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Dep. of Finance& Banking Sciences

"Forecasting Stock Market Returns via Monte Carlo Simulation: The Case of Amman Stock Exchange"

"التنبؤ بعوائد الأسهم بواسطة مُحاكاة مونتي كارلو:حالة بورصة عمان للأوراق المالية"

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"Forecasting Stock Market Returns via Monte Carlo Simulation: The Case of Amman Stock Exchange"

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Dedication

My sincerest thanks go to my family, my parents. Especially my mum for all that she had done for me, my dad for his moral support, to grandmother, uncles and aunts for encouragement. My dear brothers: Yazan & Omar have never left my side. My lovely sisters: Shatha, Hadeel, & Batool for their endless support, and love. I also would like to dedicate this work to the most special Dr. Dima AL Rabadi, for all what you do to bring this thesis into the light, and the great moments with your companion.

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Nada Ibrahim Abu Aljarayesh

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List of Abbreviations

Symbol	Subject
A	Actual Returns
ASE	Amman Stock Exchange
CLT	Central Limit Theorem
EMA	Exponential Moving Average
EMH	Efficient Market Hypothesis
f	Forecasted Returns
GBM	Geometric Brownian Motion
μ	Mean
MA	Moving Average
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MCS	Monte Carlo Simulation
RMSE	Root Mean Square Error
SE	Standard Error
SMA	Simple Moving Average
U	Theil Inequality Coefficient

Abstract

Nada Ibrahim Abu Aljarayesh. Forecasting Stock Market Returns via Monte Carlo Simulation: The Case of Amman Stock Exchange, Department of Finance and Banking Sciences, Yarmouk University, 2013(Supervisor: Dr.Dima Waleed Alrabadi).

This study investigates the ability of Monte Carlo simulation (MCs) to predict stock market returns in Amman Stock Exchange (ASE). Specifically, we compare the in-sample forecasting ability of MCs with the Simple and Exponential Moving average techniques. The data of the study consists of the daily general float index of ASE over the period (2003-2012). Forecasting accuracy is measured by four proxies: Root Mean Squared Error (RMSE), Mean Absolute Error(MAE), Mean Absolute Percentage Error (MAPE), and Theil Inequality Coefficient (U). The results indicate that MCs is the most accurate forecasting technique among the others investigated. Moreover, ASE seems to be inefficient at the weak level, given that technical analysis approaches enable investors to predict stock market returns.

Key Words: Efficient Market Hypothesis, Random variables, In-Sample Test, Monte Carlo Simulation, Simple Moving Average, Exponential Moving Average, Geometric Brownian Motion, Amman Stock Exchange.

Chapter one
General Framework

Chapter one
General Framework

1.1Introduction

Efficient Market Hypothesis (EMH) is one of the most important theories in finance. Eugene F. Fama in (1965) paper was introduced the efficient market as a market which includes a lot of rational investors, participants recognize all the current information, and security prices always fully reveal all past, public, and private available information. He said that "in an efficient market, on average, competition will cause the full effects of new information on intrinsic values to be reflected "instantaneously" in actual prices". Therefore, technical and fundamental analyses are fruitless and nugatory in predicting stock market returns.

More precisely, Random Walk Theory is a significant theory that supports the logic behind the efficient market hypothesis. It assumes that the current security price is independent from the past performance. Means that security's price reflects the present value (fair value) of its expected future cash flows. Thus, participants in the market can't earn excess returns (Fama, 1965 a).

As well, Cootner (1964) described the market efficiency as: “If any substantial group of buyers thought prices were too low, their buying would force up the prices. The reverse would be true for sellers. Except for appreciation due to earnings retention, the conditional expectation of tomorrow’s price, given today’s price, is today’s price”.

On the other hand, EMH has faced some opponents theoretically and empirically. Several studies have found some amount of predictability of stock market returns with some amount of time varying risk premiums. Others studies have found many anomalies that affect stock market returns (Malkiel, 2003).

For instance, DeBondt and Thaler (1985) compare the performance of loser and winner stocks, using monthly returns of New York Stock Exchange (NYSE) from 1926 to 1982. They find that the loser's portfolio overreacts much more than winner's portfolio over a-three year period; and the most excess returns have been generated in January.

A more clarifying example, Thaler (1987) studies the effect of January Effect for small companies. He finds abnormal returns at the end of the year and in early January. Bernard and Thomas (1990) report that expected future returns equal to returns of the similar quarter of the prior year.

Other studies have found other factors that affect the future stock returns, for example, Ito (1990) suggests that market participants differ widely from each other depending on their expectations of stock prices.

In addition, many researchers study the aspects of price and return behaviour properties in Amman Stock Exchange (ASE) as an emerging market. For instance, Alrabadi (2012) finds abnormal returns exist in (ASE) over the period 2002 to 2010, even after adjusting for market risk. In addition, Elbarghouthi *et al*. (2012) investigate the efficiency of ASE using recent econometric procedures in daily prices of its five indices, from 1st January 2000 to 31st December 2008, and find that ASE is not efficient.

Hence, forecasting stock market returns has important implications for the EMH. It provides academicians and practitioners how they can formulate their investment strategies, attain excess returns, and achieve economic stability.

This thesis examines the predictability of ASE returns over the period (2003-2012). More specifically, the study will apply three popular procedures in technical analysis: Monte Carlo simulation (MCs), Simple Moving Average (SMA) and Exponential Moving Average (EMA).

1.2 Objectives of the Study

The main purpose of this study is to examine the in-sample forecasting ability of MCs compared to other techniques such as: SMA, and EMA. In specific, it assesses the performance of the three technical techniques in predicting ASE stock market returns over the period (2003-2012). This study doesn't take in consideration the various factors that affect stock price movements in ASE such as: the global financial crisis or the Arabs spring. Therefore, this study will add beneficial information about ASE, which will help investors and traders in future to understand well the behavior of this market. It will base its forecast on the past daily free float index in ASE, and will focus only on methods of technical analysis. Thus, if we find that stock market returns are predictable using technical approaches such as MCs, then the ASE would be inefficient at the weak level.

1.3 Importance of the Study

Forecasting stock market returns is a very essential topic to both academicians and practitioners. It may have insightful indications for the determinants of stock prices, and for the EMH. Therefore, if stock market returns are predictable then investors may depend on technical analysis approaches to formulate their investment strategies. Decision

makers can also base their future economic plans on their forecasts of the stock market index returns.

1.4 Problems of the Study

The research problem can be addressed in the tow following questions:

1. Can MCs, SMA, and EMA be used as effective techniques to predict ASE stock market returns?

2. Which technique gives the most accurate forecast of stock market returns in ASE (MCs, SMA, or EMA)?

1.5 Hypotheses of the Study

To achieve the study objectives the following two hypotheses have been tested:

H_1: MCs is more accurate in forecasting stock market returns than SMA.

H_2: MCs is more accurate in forecasting stock market returns than EMA.

1.6 Structure of the Study

The structure of this thesis is as follows: chapter one provides an introduction of the study. Chapter two provides a theoretical background of market efficiency and defines the basic concepts of MCs. Chapter three reviews the related literature. Chapter four explains research methodology with its related theories. Chapter five presents the results and discussion. Chapter six documents the summary and conclusions.

Chapter Two

Theoretical Background

Chapter Two

Theoretical Background

2.1 Introduction

This chapter presents the elementary concepts of EMH and its levels, clarifies the fundamental and technical analysis approaches with their strengths and limitations, then it provides an overview of MCs as a stochastic technique to forecast stock market returns, and finally the chapter introduces ASE as an emerging market.

2.2Market Efficiency

The concept of market efficiency was first submitted by Bachelier (1900) in his PhD dissertation in math. He argues that efficient market exists only if "past, present and even discounted future events are reflected in market price". His recognition helps many scientists to develop the Brownian motion theory.

Efficient market in finance is related to the available market information. In which all relevant information is converted immediately into security prices, hence investors are unable to earn excess returns. Consequently, stock prices adjust to new information in a random manner. Moreover, their priced are equal to their intrinsic value, when

the required rates of returns are equal to the expected holding period return. Nor overvalued neither undervalued stocks (Fama, 1965 b).

Therefore, Fama (1970) divided the market efficiency into three levels, depending on the meaning of the term "all available information": the weak, semi-strong, and strong forms.

The weak form of efficiency states that current market prices already reflect and include the historical information such as: dividends and interests rates in the trading market. Therefore, technical analysis will not be practical alone to predict future prices (Malkiel, 1989).

The semi-strong form of efficiency asserts that the current market prices must reflect past and all publicly available information about the prospects of a firm. This type of hypothesis states that fundamental analysis is useless (Malkiel, 2011).

Finally, the strong form of efficiency states that the current market prices reflect all kinds of information, which is relevant to the firm (public and private). Thus, investors will not be able to realize abnormal returns or consistently find undervalued stocks (Bodie *et al*., 2013).

2.3 The Random walk Hypothesis

The challenge of random walk theory consists of understanding the behavior of stock prices (Fama, 1965 b).

Consequently, many researchers maintain that stock markets move in random trend, which means that security prices don't repeat themselves over the time. As a result, future stock prices are separated and independent in past prices (Okpara, 2010).

On the other hand, some scientists attribute that investors do not always react in proper proportion to new information. Consequently, some of them might over-react and the other might under-react to news upon their expectations (Malkiel, 2011).

In fact, investors use various strategies to beat the market. They may follow the price reversals phenomenon: what goes up must come down, and vice versa. This Phenomenon, a contrarian investment strategy, recommends investors to buy stocks that have experienced recent losses or sell stocks that have experienced recent gains. Therefore, it leads the market to correct its prices into the equilibrium line. Other phenomenon is momentum, which adopts the concept that stocks are achieving continuous excess returns (losses) at the short run. Thus, investors may earn abnormal returns by buying the winner stocks and selling the loser ones (Lo, 2007).

2.4 Forecasting Stock Market Returns

Over the past 50 years, many of financial analysts implement several kinds of squeaky research on the stock market, in the hope of achieving one goal: to beat the market. The concept of beating the market refers to realizing continuous and higher rates of return than market return and at the same level of risk (Zhang, 2004).

Therefore, accurate prediction of stock prices presents a challenging function for traders and investors. Pluralities of factors including: economic, social, political and psychological ones; interact in a complex way to form stock movement patterns (Assaleh *et al*., 2011).

More clarifying, forecasting financial time series refers to the forecast prices of a sequence of alternative financial instrument occurring over a specified period of time. Indeed, forecasting the pattern of financial time-series can be confusing and experiencing some difficulties such as: the absence of single model that monitoring dynamical changes with the passage of time, the complexity of the systems that sustain the balance between long-term and short-term trends movements during the trading process, and the determination of useful information is usually hard, because misleading information must be identified and eliminated (Zhang, 2004).

Although the EMH asserts that none of any techniques are effective to predict the market, forecasting market prices may be done following one or a set of two approaches: fundamental and technical analysis approaches. Each approach has its own advantages as well as its limitations (Malkiel, 1999).

This research aims to predict financial time series of returns in ASE through using only some technical analysis techniques.

2.5 Fundamental Analysis Approach

Fundamental analysis focuses on the causes that lead to price movements. It analyzes the macroeconomic and microeconomic factors such as: political, environment, statistics, growth rates (Gross Domestic Product), interest rates, inflation. It also depends on the analysis of financial statements: income, balance, and cash flow statements (Mcdonald, 2007).

Bodie *et al*. (2013) defines fundamental analysis as: “the analysis of the firm which uses earning, expected dividend, expected interest rates, and risk evaluation to determine the fair or the fundamental value of the stock”.

However, the primary function behind fundamental analysis is to facilitate the mission for investors, who wish to invest or beat the

market. It enables and induces traders to verify whether securities are under or overvalued (Cohen *et al.,* 2011).

Although fundamental analysis provides information about the firm's value; it has some implicit weaknesses as: collecting information is considered costly and time consuming. Also, analysts may fall under their personal preferences and bias when they conduct analysis (Zhang, 2004).

2.6 Technical Analysis Approach

The principle reason which has derived the existence of technical analysis (Chartists) is the doubts around the efficient financial markets. The logic behind technical approach stems from the belief of the price movements behavior. Chartists have contradicted the random walk theory. They claim that prices have certain movements' patterns, in which prices are not totally random and history can repeat itself (Zhang, 2004).

Technical analysis is concerned with the study of past trading information to make a price forecast such as: the movements of common stock prices and the volume of trading. This approach adopts the belief that all historical information of a firm is automatically reflected in the firm's past market prices (Malkiel, 1999).

Moreover, chartists analyze investors sentimental (fear and greed) in the marketplace, While fundamentalists focus on analyzing the data which is related to the firm. Hence, they don't use their experience and expectations on the stock prices change, neglecting the fact of how market prices are changed. They assume that investors act in rational manner at all times (Brown, 2003).

2.7 History of Monte Carlo Simulation

Monte Carlo method conception has derived its roots in the early of 1940s, concurring with the revolution of electronic computer. Indeed, the modern term of Monte Carlo has received a lot of attention by J. Neumann, S. Ulam, and N. Metropolis, the American mathematicians, during the Manhattan Project of World War II (nuclear weapon projects) at Los Alamos National Laboratory. Therefore, Monte Carlo then is related to atomic bombs work. Metropolis has inspired the name from the Monte Carlo Casino, where Ulam's uncle often gambled, because of the similarity functions between the stochastic simulations and the game of chance (Metropolis, 1987).

In 1977 the Monte Carlo method (stochastic simulation) was introduced in finance, in the pioneering work of Boyle (Krykova, 2003).

Nowadays, after the technological revolution applying simulations has become easier, and give almost accurate results. As a result, many numerical problems in science, economics, finance, physics, chemistry, and engineering can be solved by Monte Carlo technique (Kroese, 2011).

2.8 What is Monte Carlo Simulation?

Monte Carlo methods are statistical techniques which are sufficient to solve a complex mathematical or statistical problem. The logic behind MCs is creating sequences of random numbers to perform statistical simulation with generating new configurations of a system of interest, over long periods of real time (Rollett & Manohar, 2004).

Moreover, the primary function of MCs is to minimize the variance by averaging the results of large numbers of samples, even when the Convergence is slow (Lafortune, 1996).

Simulation facilitates solving many problems in financial engineering, which focus on estimating a certain value such as: pricing derivative securities, computing price sensitivities, and evaluating portfolio risks. Consequently, MCs is a stochastic method that is often applied to approximate expectations. In fact, MCs is applied by three essential steps: generating sample paths randomly, evaluating the payoff

along each path, and calculating an average to attain estimation (Chen & Hong, 2007).

2.9 Advantages of Monte Carlo Simulation

In this part, the benefits and drawbacks of MCs will be presented compared to other numerical methods. MCs has several advantages as follows:

1. Applying MCs is easy and flexible to solve a complex financial problem (Boyle *et al*., 1997).

2. Applying MCs is often being attractive to deal with problems that have many dimensions, because its rate of convergence does not depend on the dimensionality of the problem (Chen & Hong, 2007).

3. The execution of MCs does not consume a lot of time because of the increasing speed of computer programming (Whiteside II PE, 2008).

4. MCs is free from the restrictions of solving Newton's equations of motion. This freedom allows generating trial configurations within the statistical mechanics ensemble of choice (Earl & Deem, 2008).

2.10 Limitations of Monte Carlo Simulation

On the other hand, the limitations of MCs including the following:

1. Inappropriate inputs such as: standard deviations and correlations, can lead to wrong simulation results (Ibbotson Associates, 2005).

2. There are a number of unknown factors that simulation can’t be truly accounted for during an investor’s lifetime (Ibbotson Associates, 2005).

3. MCs is troubled from its ability to model serial correlation between what comes out and what was just drawn, because there is no way to control variables. So that, the user should be prepared to make the necessary adjustments if the results that are generated seem out of line (Ibbotson Associates, 2005).

4. Because Newton’s equations of motion don't solve, therefore no dynamical information can be gathered from a traditional MCs (Earl & Deem, 2008).

5. MCs may hold some a statistical and systematic error (Umrigar, 2010).

2.11 Amman Stock Exchange

Hence forecasting price movements in emerging markets have several features as: being more elusive, more volatile, often accompanied by thin trading-volumes and it is susceptible to more manipulation compared to mature markets (Assaleh *et al*., 2011). This part introduces the properties of ASE as an emerging market, and clarifies the study objectives.

In 1976 until 1997 ASE was known as Amman Financial Market (AFM). The Law No. 31 which was issued in 1976 verified the objectives of AFM as: mobilizing savings by encouraging investment in securities, and regulating the issuance of and dealing in securities in a manner that would ensure the soundness, ease and speed of transactions to safeguard national financial interests and to protect small savers. Then ASE was established in March 11-1999 as a result of the reformation process of the Jordan Capital Market. It is described as a non-profit, private organization with administrative and financial independency, authorized to exchange trading securities. In addition, ASE is an efficient market for trading securities, hence it offers an attractive and safe environment for investment, develops processes and systems of trading securities in the stock market, meets the newest international standards, and publishes trading information to the largest possible number of participants[1].

Then in 1997 the Law, No.23 was issued as a turning point for the Jordanian capital market. The vital feature of this restructuring effort was the separation of the supervisory and legislative role from the

[1] www.ase.com

executive role of the capital market. The Law offered three new institutions to replace AFM, which are:

1. Jordan Securities Commission (JSC)
2. Amman Stock Exchange (ASE)
3. Securities Depository Center (SDC)

JSC is responsible of identifying regulations and monitoring the market. SDC is responsible of managing settlements and maintenance of ownership records. In fact, ASE is one of the largest stock markets in the region that allows foreign investment. Therefore, Table 2.1 shows the size of trading in ASE according to the statistics of 2012[2]:

Table (2.1)

Size of Trading Development in ASE*

Subject	Value
Number of current exchange shareholders	**778,760**
Percentage of shares owned by Jordanian companies and individual investors	**48.8%**
Percentage of foreign investors ownership	**51.2%**

* Source: Table prepared by researcher

Indeed, there are certain obligations that must be met before a corporation can be listed in the first market of the ASE such as: the corporation must have made a pre-tax profit for at least two out of the

[2]www.ase.com

three years before being listed. Moreover, the corporation must accomplish certain requirements relating to the free-float and number of its stocks. Also, investors must be able to easily sell their stocks through the stock exchange. On the other hand, firms can list their shares at the Second Market after they attain the right to start their operations from the Ministry of Industry and Trade.

In fact, ASE has become larger year after year in the secondary market trading from 1978 compared to 2012, as it shows in the following Table (2.2)[3]:

Table (2.2)

Main Developments Occurred in ASE from 1978-2012*

Subject / Year	**1978**	**2012**
Trading on the secondary market	**JD286 million**	**JD2.0 billion**
Market capitalization (shares-x price)	**JD286 million**	**JD19.1 billion**
Number of listed companies	**66**	**243**

* Source: Table prepared by researcher

The number of companies increased from 66 in 1978 with a market capitalization of JD 286 million to 243 companies in 2012 with a market capitalization of JD 19.1 billion.

[3]www. ase.com.jo

Chapter Three

Empirical Studies

Chapter Three
Empirical Studies

3.1 Introduction

This chapter reviews a number of studies that use different prediction approaches. Many studies have found significant signs of the ability of prediction in different stock markets with different techniques. In this section, studies will be classified into two different categories basing on its technique: Technical approach, and Fundamental approach.

3.2 Empirical Studies

A. Empirical Studies of Technical Approach

Kim (2003) applies an advanced method called: Support vector machines methods (SVMs), to predict the stock price index. He uses 12 technical indicators of the daily Korea composite stock price index (KOSPI) over January 1989 to December 1998. The study investigates the feasibility of applying SVM in financial forecasting by comparing it with back-propagation neural networks and case-based reasoning. This method is considered important for the prediction of financial time series because they use a risk function consisting of the empirical error

and a regularized term which is derived from the structural risk minimization principle. The empirical results show that SVM provides a promising alternative to stock market prediction.

Koopman *et al*. (2005) explore the forecasting value of historical volatility (extracted from daily return series), implied volatility (extracted from option pricing data) and realized volatility (computed as the sum of squared high frequency returns within a day). Their data consist of the Standard & Poor's 100 (S&P 100) stock index series during the period from 6 January 1997 to 14 November 2003, which constitutes a total of N=1725 trading days. They apply the unobserved components and a simple long memory model of realized Volatility (UC-RV) [4].The predictive abilities of realized volatility models are compared with those of stochastic volatility (SV) models and generalized autoregressive conditional heteroskedasticity (GARCH) models for daily return series. The experimental outcomes show persuasively that realized volatility models produce more accurate volatility forecasts compared to models based on daily returns. Long memory models appear to supply the most accurate forecasts.

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[4]UC-RV: is regarded as an accurate estimator of volatility.

Atmeh and Dobbs (2006) investigate the performance of fourteen moving average trading rules in forecast future prices. The study utilizes bootstrap methodologies such as: the random walk model, AR (1)[5], and GARCH-M. The data of this study represents the daily general index of ASE over the period 1992 to 2001. The results suggest that technical trading rules can assist to forecast market movements, with evidence that the short run rules may be profitable even after allowing transactions costs. In addition, the returns that were generated by the bootstrap reveal that the actual trading profits are not consistent with those that might be generated by the random walk or AR(1) methods.

Hartmann and Pierdzioch (2007) investigate the relationship between exchange rate movements and stock returns. They use a recursive modeling approach: the adjusted coefficient of determination (ACD), the Akaike information criterion (AIC), and the Bayesian information criterion (BIC) during the period from 1991–2005 based on monthly database of Japan market. They find that the exchange rate movements per second do not help to explain stock returns. Tests of in-sample-predictability of stock returns have revealed a significant link between exchange rate returns and 1-month-ahead stock returns. Finally

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[5] The autoregressive model

a recursive modeling approach and tests of market timing have revealed that the evidence of in-sample predictability of stock returns does not necessarily constitute a violation of market efficiency.

Döpke *et al*. (2008) provide an evidence of the ex-ante predictability of monthly excess stock returns in Germany, based on real -time macroeconomic data from 1994 to 2005. Recursive modeling approach has been applied in order to forecast stock returns in real time while Sharp, Treynor, and Jenson's ratios have been applied to measure the performance of stock returns. They have found that the return which is predicted based on real - time macroeconomic data is the same as the return based on revised macroeconomic data. Furthermore, the performance of portfolio switching strategies based on the preceding real – time macroeconomic data is the same as the performance based on revised macroeconomic data.

Ajlouni and Al-Hawarei (2010) provide an evidence of non-efficiency of ASE at the weak level using first - order serial correlation, over the period 2001 to 2008 in 101 listed companies. The data consist of daily, weekly, monthly, and yearly closing prices. Their results conclude that ASE is not efficient at weak level. The serial correlation is not significant at 5%, and the returns in ASE are repeating themselves for the most times.

Tsao Pan (2010) proposes an analysis method based on a hybrid model to enhance prediction ability. The hybrid model merges the principal component regression (PCR) model and the general regression neural network (GRNN) to resolve both multicollinearity problems and non-linear problems at the same time. The study sample includes the daily stock information of Taiwanese and Chinese companies from 3 August 2004 to 26 March 2008. The study uses ten financial ratios: turnover of receivables, inventory turnover, fixed assets turnover, current ratio, acid-test ratio, debt ratio, net profit ratio, return on asset ratio, long-term capital to fixed asset ratio and sales/shares. For the test results, the researcher has calculated the five indices: the root mean square error, revision theil inequality coefficient, mean absolute error, mean absolute percentage error and coefficient of efficiency. The empirical results show that the prediction power of the hybrid model of PCR genetic algorithm general regression neural network is more powerful than the model of PCR, GRNN and PCR + GRNN.

Ali *et al*. (2011) use the artificial neural network in modeling stock prices. This study applies simulation for seven Jordanian companies listed in ASE selected from (service and manufacturing sectors); to evaluate the network performance. The model was evaluated by stock market brokers through the use of a questionnaire that was

distributed in Amman Stock Exchange. For each company, a full year was used for training the network, and another for validation of results. The results show that the network is able to produce the output within a MSE of $0.0023*10^{-8}$ from the target. The network output (forecasted prices) is very close to the actual data (price) except for the last month where the actual price has a small drop. The majority of the respondents stated that they may depend on ANN technique and that they believe that the technique is applicable to all categories of companies.

Assaleh *et al*. (2011) present two prediction models for predicting securities' prices. The study is conducted on Dubai Financial Market (DFM) as an emerging market, and applies to two of the market's leading stocks. These two leading stocks are: Emaar Properties (EMAAR) and Dubai Islamic Bank (DIB). EMAAR is the leading real estate developer in the Middle East and DIB is the world's first fully fledged Islamic bank. These stocks were chosen because they have sufficient historical data, actively traded, and each represents a different sector in the UAE economy. The study uses daily closing prices over the period from April 2000 to March 2006 (a total of 2176 data points). They use two special models: Artificial Neural Networks (ANN), the second model is Polynomial Classifiers (PC) as modeling techniques to predict stock prices from historical price data. This was the first time to

apply PC to be used in stock prices prediction. Both models use the same inputs and the data for both models is identical. Results indicate, in general, that both models are effective. Very good results are found in terms of mean absolute error percentage. Both models reveal an average error around 1.5% when predicting the next day price, an average error of 2.5% when predicting the second day price, and an average error of 4% when predicting the third day price.

Giovanis (2011) examines several investment strategies based on four different prediction approaches of stock returns: the moving average, the Moving Average Convergence-Divergence, a random walk autoregressive model, and the model that he has proposed; Generalized Autoregressive Conditional Heteroskedasticity (GARCH) regression with Wavelet decomposition and Monte Carlo simulations algorithm developed in MATLAB. He uses five major stock market indices (S&P 500 for U.S.A., FTSE-100 index for UK, DAX index for Germany, CAC-40 for France and NIKKEI-225 for Japan),based on daily data of closing price returns. The period of estimation starts from 3, January 1950 for S&P 500, 2, April 1984 for FTSE-100, 26, November 1990 for DAX, 1, March 1990 for CAC-40 and 4, January 1984 for NIKKEI-225. The ending time period for the estimation is similar for all estimations and it is 30, October 2009. The remaining period from 2, November

through 13, November 2009 is obtained as the forecasting test period, which is actually 10 trading days. The empirical results reveal that the procedures MA and MACD might lead to net profits, but not in all cases. In addition, moving average of 1-30 provides the best forecasting performance comparing with the other two possible moving averages. In contrast, random walk autoregressive model leads in all cases to net losses. Finally, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) regression with Wavelet decomposition and Monte Carlo simulations model lead always to net profits and give significant higher profits in three stock indices than the other techniques.

Kara *et al*. (2011) investigate the predictability of financial movement direction with artificial neural networks (ANN) and support vector machines (SVMs) by predicting the daily closing price movement of Istanbul Stock Exchange (ISE) National 100 Index. The period from January 2, 1997 to December 31, 2007 has been covered. The experimental results show that both techniques have given significant performance in predicting stock price movements, but ANN model gives better performance than SVM.

B. Empirical Studies of Fundamental Approach

Numerous studies have investigated the possibility of using different methods of forecasting stock returns over the last 20 years. For instance, Choi *et al*. (1999) attempt to explore the relationship between industrial production (IP) growth rates and lagged real stock returns. They use monthly observations of the aggregate stock price index, industrial production index, and consumer price index of the G-7 nations: Canada, France, Germany, Italy, Japan, the UK and the US, over the period January 1957 to March 1996. They apply both in-sample cointegration and causality tests, and an out-of-sample forecasting procedure introduced by Ashley *et al*. (1980). They find that the cointegration tests reflect a long-run equilibrium relationship between the log levels of IP and real stock prices, while the error-correction models show an association between IP growths and lagged real stock returns for all nations except Italy.

Furthermore, Lewellen (2004) uses different types of financial ratios to predict aggregate stock returns. The study covers different periods from 1946 to 2000 for dividend yield and from 1963 to 2000 for book to market and earning to price ratios. By implementing predictive regression approach, the results remain strong despite the unusual price run- up in the recent years of the study.

Belke and Polleit (2004) examine the ability of dividend yields to predict future stock returns. This study has been applied on German stock market returns. The period extends from August 1974 to September 2003, based on monthly data. This study utilizes the method which is proposed by Pesaran, Shin and Smith (1996). The process is generally known as: an autoregressive distributed lag (ARDL) model. This procedure is new and refers to test for cointegrating relationships among future stock returns and today's dividend yield. It is efficient for small samples and capable of dealing with the controversial issue of exogeneity of the dividend yield. They state that the dividend yield has a statistically significant positive impact on the future stock returns in Germany. The power of dividend yields to forecast future stock returns increases with the return horizon.

Moreover, Rapach *et al.*(2005) investigate the predictability of stock returns using macroeconomic variables such as: interest rate, inflation, the term spread, industrial production, money stocks, and unemployment rate in 12 industrialized countries based on monthly data. The period begins in the early-to-mid 1970s and end in the late 1990s. The study utilizes both in-sample and out-of-sample tests of predictive proficiency, with the out-of-sample outlook period covering

the 1990s for each country. The results show that, interest rates are the most consistent and reliable predictor of stock returns across countries.

However, Elleuch (2009) examines whether fundamental analysis based on historical accounting information has the ability to predict future returns and future earnings performance. The primary purpose of this study is to investigate the ability of historical data to change the distribution of returns earned by investors. The study provides evidence that accounting-based fundamental signals can be used to predict future stock returns. Thus, investors will separate winner stocks from loser stocks through simple fundamental analysis strategy. The strategy consists of 12 fundamental signal ratios such as: inventory, account receivable, investments, gross margin, labor force, return on assets, cash flows, accruals, leverage, liquidity, and assets turnover. The study is applied on the Tunisian stock market including 22 non-financial firms. Financial statements over the period 1993 to 2001 are used to test the prediction ability. The results show that fundamental signals have positive and significant correlation with future earnings performance and it is able to discriminate between winner and loser portfolios.

Kheradyar and Ibrahim (2011) investigate the role of financial ratios as empirical predictors of stock return. Panel data model and generalized least square techniques were used to estimate the predictive

regressions in separated and combined models. The study examines the Malaysian bursa over the period January 2000 to December 2009. They find that book to market ratio show better ability to predict stock return than dividend yield and earning yield. Also, a combination of financial ratios enhances stock return prediction.

Ferreira and Santa-Clara (2011) examine forecasting stock market returns by three financial components separately. They use the sum-of the-parts (SOP) method; that consists of the following ratios: dividend–price ratio, earnings growth, and price–earnings ratio growth rate. Moreover, Monte Carlo simulation has been applied to compare the performance of the SOP with the historical mean and predictive regression methods. The SOP method has applied on the same data as Goyal and Welch (2008).They use monthly and yearly (non-overlapping) data to predict the stock market returns. The study sample has taken from the S&P 500 index returns over the period from December 1927 to December 2007 with annual data. The analysis is repeated on Global Financial Data (GFD) for the U.K. and Japan over the period is from 1950 through 2007. The results come up as: the restricted versions of the predictive regressions, both the dividend-price ratio and the earnings growth components are equally responsible for the performance of the SOP method. Also, the performance of the SOP

method is robust to alternative estimates of the persistence of the dividend-price ratio and of the average earnings growth. In addition, the results in subsamples and the international data have been robust. The performance of SOP method, in the U.S is stronger more than Japan and UK, even though they show their ability to predict stock returns. The trading strategy that uses the simplest version of the SOP method is considerable. Its certainty equivalent gain is 1.8% per year and the Sharpe ratio is more than 0.3% higher than a trading strategy based on the historical mean. Moreover, Monte Carlo simulation shows that the root mean squared error of the SOP method is 2.87%, compared to 4.94% for the historical mean and 3.73% for predictive regressions. Obviously, the average returns are driven mostly by earnings growth and the dividend-price ratio. Finally, most of the return volatility stems from earnings growth and the price-earnings ratio growth.

Al-khatib and Al-Horani (2012) investigate the role of a set of financial ratios in predicting financial distress of publicly listed companies in ASE. They use multiple discriminate analysis and logistic regression together with 24 ratios. The study covers the period from 2007 to 2011. The results show that both logistic regression and discriminate analysis are able to forecast financial distress. Also, Return on Equity (ROE) and Return on Assets (ROA) are the most important

two financial ratios that are useful in predicting the financial distress of public companies listed in ASE.

Gupta and Modise (2012) investigate the in-sample and out-of-sample prediction ability of five financial variables and six global stock returns: Price–dividend ratio, Price–earnings ratio, Treasury bill rate, Term spread, Payout ratio, S&P 500, FTSE 100 Index, Nikkei 225, and Hang Seng Index, DAX, CAC. They use monthly data of South African stock returns over the period 1990 to 2010. To obtain critical values of data mining; they use the robust bootstrap procedure, which is used by Rapach and Wohar (2006). For in-sample predictions; they use the regression model, while for the out-of sample, the MSE-F[6] and the ENC-NE[7]are utilized. Their findings state the following: the predictive ability of stock returns will not be improved by adding more financial variables. Moreover, the results of the forecasting ability have been varied for the in-sample and out of sample tests. The in sample tests show that only the stock returns for South Africa have predictive power at the short and the long run horizons. While the out-of sample tests; show some predictive ability at certain horizons in South Africa stock

[6]MSE-F: the McCracken (2004) MSE-F statistic, a variant of the Diebold and Mariano (1995) and West (1996) statistic designed to test for equal predictive ability.

[7]ENC-NEW:the Clark and McCracken (2001) ENC-NEW statistic, a variant of the Harvey, Leybourne, and Newbold (1998) statistic designed to test for forecast encompassing.

returns with the Treasury bill rate and the term spread. The MSE-F and the ENC-NEW test statistics become insignificant from six months – a head horizon. Also, the S&P 500 and the FTSE 100 are the main stock returns which explain movements in South Africa's stock returns.

AL- Shubiri (2013) analyzes the relationship between economic variables and abnormal stock returns of industrial firms listed in ASE. The five macroeconomic variables that are tested to influence stock abnormal returns are: money market interest rate, money supply, industrial production index, gross fixed capital formation, consumer price index. The idiosyncratic risk factors are: market risk; size price-to- earnings ratio; and price to - book ratio. The study uses a multiple regression model, based on the monthly data from 2005 to 2011. The results show a co-integrating relationship between macroeconomic variables and stock prices. In addition, interest rate, industrial production index, and gross fixed capital information show a negative effect on abnormal returns index. While, money supply do positively influence Index. On the other hand, consumer price index does not appear to have any significant effect on ASE Index returns.

Shubita (2013) examines the forecasting ability of earnings and operating cash flows. The sample of this study includes 66 Industrial companies listed in ASE, 362 firm-year observations, for the period

2006-2011. Four OLS regression models are applied to predict the relationship between earnings and operating cash flows measures. Model 1 aims to examine the relationship between future operating cash flow and current earnings. Model 2 studies the link between future operating cash flows and current earnings plus depreciation cost. Model 3 investigates the relationship between future operating cash flows and current working capital. Finally, model 4 investigates the relationship between future operating cash flows and current operating cash flows. The study results indicate that earnings along with depreciation and amortization expenses are the greatest predictor of all future cash flows in comparison with net income and reported operating cash flows. In addition, the forecasting ability of the reported operating cash flows in large firms is greater than small firms.

3.3 What distinguishes this study from previous studies?

The importance of this study comes from the lack of similar ones that use technical analysis approaches to forecast stock returns in ASE as an emerging market. To the best of the researcher's knowledge this is the first study that uses MCs to predict stock market returns in ASE. Thus, predicting future returns is a very critical subject to academicians, investors, policy makers and for all other parties who are interested in ASE. Time series analysis, SMA technique, EMA technique, and MCs are used for forecasting the stock market prices. However, their performance depends on the forecasting accuracy measurements. The motivation of this research is to introduce the concept of MCs into the Jordanian sector, and utilize it in forecasting the Jordanian stock market prices. In other words, it appears to be worthy to provide researches with what are the technical techniques that can be used to accurately predict stock market returns in ASE? This research will attempt to answer two important questions:

1. Can technical techniques predict stock market returns of ASE, and if so which of these techniques are most accurate?

2. Does the application of MCs provides a better method for predicting stock market returns in ASE compared to SMA and EMA?

Chapter Four

Data and Methodology

Chapter Four
Data and Methodology

4.1 Introduction

This chapter presents our methodology. It gives an introduction of the mathematical theories, which are relevant for performing MCs in a financial setting. In addition, it explains the empirical forecasting techniques and then clarifies how the comparison methods are applied.

4.2 Data of the Study

The data of this study consists of the daily values of the free float market index in ASE over the period (2003 – 2012). This index reflects the stock prices of the firms that are traded and excludes the non – traded stocks, thus it is an accurate index.

This index was given the base value of 1000 points as the closing of the year 1999. It is based on the free float shares. It implies only the market value of the free float shares of the companies, not the total number of listed shares of each company. The following formula is used to calculate this general index, $Index_t$:

$$\text{Index}_t = \frac{\sum_{i=1}^{n} P_{ti} \times S_{ti} \times F_{ti}}{D_t} \qquad (4.1)$$

Where P_{ti} is the closing price of company i on day (t), S_{ti} is the number of listed shares of company i on day (t), F_{ti} is the factor of the company i on day (t), and D_t is the divisor index on day (t).

The factor (F) is a number between zero and one. The estimation of this factor relies on the company free-float ratio that reflects the total listed shares minus the shares owned by the board of directors, investors who own more than 5% and any government ownership. The rate of factor (F) is adjusted quarterly by the ASE at the time of index re-balancing.[8]

4.3Some Mathematical Theories(A preface)

4.3.1The Basics of Monte Carlo Method

Generally speaking, a Monte Carlo technique can be defined as any technique which using random numbers to solve a problem. It can deal with either probabilistic or statistical problems (James, 1980).

[8]http://www.ase.com.jo

Halton (1970) has defined Monte Carlo method as a method that represents the explanation of a problem as a parameter of a hypothetical population and using a random sequence of numbers to create a sample of the population, from which statistical estimates of the parameter can be obtained.

Therefore, Simulation in general is known as a numerical technique for conducting experiments in the computer, involving random sampling from probability distributions (Davidian, 2005).

Essentially, the concept of MCs is based on the strong law of large numbers and the central limit theorem (see the next part). More precisely, the Law of Large Numbers assumes that as the sample size increase thus the sample mean is forced to be closer and closer to the population mean μ(BelginSert, 2011).

4.3.2 Monte Carlo Integration

In finance the MC method is particularly useful because of its ability to estimate integrals. Since, it is a way to solve multidimensional integrals (Cowan, 2009).

Sometimes Monte Carlo integration is called as MCs. It is a powerful method for computing the value of complex integrals using

probabilistic techniques. Applying simulation is considered simple, easy, and direct method to use (BelginSert, 2011).

The convergence rate of MCs equals $O(N^{-1/2})$, which is independent of the dimension of the integral. Thus, MC method is a robust method, and its accuracy depends only on the crudest measure of the complexity of the problem. So, it can be extremely slow (Caflisch, 1998).

According to Glasserman (2003), MC methods use random numbers to estimate the volume of an integral. The integral of a function $f(x)$ can be stated as the average or expectation of the function f evaluated at a random setting. An integral on the one-dimensional unit interval can be written:

$$I[f] = \int_0^1 f(x)dx = \bar{f} \quad (4.2)$$

Let x; be a random variable that is uniformly distributed on the unit interval. Then,

$$I[f] = E[f(x)] \quad (4.3)$$

For an integral on the unit cube $I^d = [0,1]^d$ in d dimensions,

$$I[f] = E[f(x)] = \int_{I^d} f(x)dx \quad (4.4)$$

in which x is a uniformly distributed vector in the unit cube.

The Monte Carlo quadrature formula is based on the probabilistic interpretation of an integral. Consider a sequence $\{x_n\}$ sampled from the uniform distribution. The empirical approximation of Monte Carlo integration can be written as follows(Caflisch, 1998):

$$I_N[f] = \frac{1}{N}\sum_{n=1}^{N} f(x_n) \qquad (4.5)$$

According to Feller (1971), the Strong Law of Large Numbers predicts that the estimate converges to its true value as the sample size increases. The approximation is convergent with probability one,

$$\lim_{N\to\infty} I_N[f] \to I[f] \qquad (4.6)$$

In addition, it is unbiased, which means that the average of $I_N[f]$ is exactly $I[f]$ for any N; that is,

$$E[I_N[f]] = I[f] \quad (4.7)$$

Where, the average is over the choice of the points $\{x_n\}$.

4.3.3 Random Variables

Since random variable is essential to apply Monte Carlo technique; random variable definition and its characteristics will be explained briefly in this part.

The idea of MCs stems from simulating a large number of variables, and then finds out the average of the desired quantities. Hence, the behavior of the process and the distribution type will be known. Thus, the purpose of Monte Carlo process is to figure out an expected value of a random variable (BelginSert, 2011).

The concept of a random variable defined as a real number x_i that is assigned to an event E_i, where the event and the values are random and may vary over the real axis (Robert & Casella, 2010).

Other definition provides by Boas in (1996), he describes a random variable as a function on a sample space that maps every sample point to a real number, can be discrete or continuous.

Furthermore, a random variable or a stochastic variable is any possible value has been chosen coincidently and its value is unpredictable. In other words, the question which can't be answered: how do these variables have selected? However, the probable value is unpredictable but in some way the distribution of the variable can be known (James, 1980).

The distribution of a random variable gives the probability of a given value (or infinitesimal range of values). The continuous variables can be described as:

$$\int_{-\infty}^{\infty} f(x)dx = 1 \qquad (4.8)$$

Where x is a random variable and $f(x)$ is the probability density function (pdf).

In fact, random variables are known as pseudo random numbers if one doesn't be able to generate uniformly distributed random numbers. These pseudo-random numbers are identified as random varieties or stochastic varieties. One of the familiar approaches of generating random variables is to use a mathematical algorithm. They can be easily implemented in a computer program. These algorithms produce numbers in a deterministic and entirely predictable way; means that they are reproducible. In spite of the deterministic fashion; these numbers seem to be random because they attain a number of statistical experiments, designed to analysis a variety of properties of random numbers (Perros, 2009).

For simplicity in this study, we will submit to pseudo-random numbers as random numbers.

4.3.4Central Limit Theorem

The Central Limit Theorem (CLT) relates the sample mean of a sufficiently large number of random variables to the normal distribution. It says that the distribution of any sample will be Normal, no matter

what is the distribution of the original data. In other words, if S_n is the sum of n mutually independent random variables, then the distribution function of S_n is well-approximated by a certain type of continuous function known as a normal density function (Lapeyre, 2007).

Feller (1971) describes the size and statistical properties of Monte Carlo integration errors depend on CLT as:

For N large,

$$\varepsilon_N[f] \approx \sigma N^{-1/2} \nu \qquad (4.9)$$

In which, ν is a standard normal $N(0,1)$ random variable and the constant $\sigma = \sigma[f]$ is the square root of the variance of f ; that is,

$$\sigma[f] = \left(\int_{I_d} (f(x) - I[f])^2 dx \right)^{1/2} \qquad (4.10)$$

This says that the error in Monte Carlo integration is of size $O(N^{-1/2})$ with a constant that is just the variance of the integrand f. Moreover, the statistical distribution of the error is approximately a normal random variable (Caflisch, 1998).

4.4The Basic Methodology

4.4.1Stock Market Returns Time Series

This study measures the prediction performance through using tests of in-sample period. Thus, it uses the free float index as the benchmark for comparing the rates of return .

The daily rates of return for time series (the continuously-compounded returns) have been calculated by using the following formula (Das, 2010):

$$R_t = \ln\left[\frac{S_t}{S_{t-1}}\right] \qquad (4.11)$$

Where R_t is the market rate of returns at day t, $S(t-1)$ is the index price (value) at day t-1/ historical price, and $S(t)$ is the index price (value) at day t / recent price. Therefore, by applying the preceding equation (4.11); we get the daily rates of return (Actual returns) for the study period (2003-2012).

4.4.2 Forecasting Techniques

This part will explain the forecasting techniques that we use in this study. Indeed, the forecasting techniques are used: SMA of 2-days,

SMA of 3-days, SMA of 5-days, SMA of 10-days, EMA of damping factor 20%, EMA of damping factor 30%, and MCs.

A. Moving Average Techniques

Moving average (MA) method is one of the most popular methods of technical analysis. It is an easy method to quantify and apply in investment decision-making or empirical tests. Technicians utilize MA method in order to give indication of buy or sell signals (Shachmurove *et al*., 2001).

For instance, the price may follow either an uptrend or a downtrend. As a result, technicians' define an uptrend as a period of rising recent prices than older prices. While a downtrend as a period of falling recent prices than older prices. Thus, they believe of buying signal when the price is following the uptrend and vice versa (Toms, 2011).

A MA is calculated as an average of observations from a number of subsequent time periods. MA method is smoothing out the irregularities in the data series. However, there are three types of MA: simple (arithmetic), weighted (linear) and exponential (Shachmurove *et al*., 2001).

In this thesis, we apply two kinds of MA: the SMA and the EMA. This part will start with the SMA.

1. Simple Moving Average

A SMA is the average of a price series over a selected time period which gives an equal weight to each period price. The mechanism of SMA includes the market movement forward in time; the oldest price is removed from the MA calculation and replaced by the most recent price (Mendelsohn, 2000).

For n -period; SMA forecast serves as an estimate of the next period value. ASMA (Forecasted value) f at time n of a signal A (Actual value) is expressed as follows (Giovanis, 2011):

$$f = \frac{1}{n}\sum_{i=0}^{n-1} A(n-i) \qquad (4.12)$$

Where n is the time interval over, which the average is computed. It is easy to show that if the trend of $A(n)$ is positive, the moving average f will be below A, while f will be larger than A when the trend is negative.

2. Exponential Moving Average

EMA has enhanced the lag of SMA. It solves the equal-weight problem of the SMA. While the SMA gives the same weight for every point whether recent or old data series; EMA gives greater weights to more recent data; the weight of the past data declines exponentially (Brooks, 2006).

The following equation defines the general expression of single EMA (Cargal, 1988):

$$f_{t+1} = (1-\alpha)A_t + \alpha f_t \qquad (4.13)$$

Where f : is the forecast value, α is the smoothing constant (0< α <1), the larger the α , the more weight is given to recent observation (damping factor), and A is the actual value.

In this study, we apply the single EMA with different value of damping factor (α) as Microsoft Excel definition. The default damping factor is 30%. Values of 20% to 30% are reasonable smoothing constants. These values signify that the current forecast supposed to be adjusted 20 percent to 30 percent for the error in the previous forecast. It is a corrective factor that minimizes the instability of data that is collected across a population.

B. Monte Carlo Simulation

This section will describe every step of Monte Carlo implementation with respect to the current study. Mechanisms of MCs can be reviewed as the following (Krykova, 2003):

1. Mean and Standard Deviation

First we calculate the average daily return and the standard deviation of returns for a certain period of time repeatedly (we assume it one month for the purposes of this thesis). The average of any sequence of variables x is the expected value of that variant x; which is known as the mean value or arithmetic mean. It is the center of gravity of the distribution, and usually it is denoted by the Greek letter μ. In statics the mean value of observations equals (Krykova, 2003):

$$\mu = \frac{1}{n} \sum_{i=1}^{n} (x_i) \qquad (4.14)$$

Where, N is the finite number of variant values, x is any random number, and i can take on any value from 1 to n.

On the other hand, the variance σ^2 measures the spread of a distribution. It quantifies the amount of variability around the mean value. The empirical variance equals (Das, 2010):

$$\sigma^2 = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \mu)^2 \qquad (4.15)$$

Therefore, the standard deviation is the positive square root σ of the variance, and is the standard measure of stochastic uncertainties.

$$\sigma = \sqrt{\sigma^2} \qquad (4.16)$$

2. Generating Random Variables

Second, we use the function "RAND", in which it used in Microsoft Excel to estimate a random number on a daily basis.

The procedure of generating sequences of random numbers is to create an artificial environment to specify the values of important parameters, and the nature of the chance process. Then the computer will run the chance process over and over, finally it will demonstrate the results of the test (Barreto & Howland, 2006).

3. Geometric Brownian Motion (Stochastic Process)

Third, we sum the average return with a random shock of return calculated by multiplying the standard deviation by the random value estimated in the second step. Finally, in order to calculate the forecasted price in day t+1, we multiply the actual price on day t by the exponential

value of the sum calculated in the third step. The forecasted returns are calculated following the formula (Choong, 2012):

$$\ln(S_t / S_{t\text{-}1}) = \mu + z\sigma \quad (4.17)$$

Where

- μ : is the constant (deterministic component) daily mean of return which is calculated on month- by- month basis (drift).
- Z: is the pseudorandom number (stochastic component).
- σ : is the monthly volatility; it expresses the stochastic random shock.

The Brownian motion process assumes that the forecasted return is a function of the historical mean return (drift) plus a random stochastic shock in returns (volatility). For simulation process; we apply the previous process 1000 times, and then the average of these iterations are found.

Brownian motion is one of the most primary and fundamental stochastic processes in modern quantitative finance. It is named after the English Robert Brown, who was the first one that studied and noticed this motion in 1827. Later, it was studied by Albert Einstein who provided an explanation of Brownian motion. After that, it was applied mathematically by Norbert Wiener. Therefore, it is often called the Wiener process (Leeuwaarden & der Pol, 2011).

The basic continuous-time model for financial asset prices; assumes that the natural log-returns of a given financial asset follow a Brownian motion with a drift (BelginSert, 2011).

As a result, A Geometric Brownian Motion is defined as a stochastic process $S(t)$ solves the following stochastic differential equation. It assumes that stock prices follow a (continuous time) geometric Brownian motion process (Fanning &Parekh, 2004):

$$dS(t) = \mu S dt + \sigma S dW(t) \qquad (4.18)$$

Where,

- S : is the current stock price.
- $dW(t)$: is a Brownian motion.
- μ : is constant and represents drift (the expected stock returns).
- σ : represents stock return volatility.

While the equation of Geometric Brownian Motion (GBM) is natural log-normally distributed; it takes on only non-negative values:

$$S(t) = S(0)e^{(\mu-\frac{1}{2}\sigma^2)t+\sigma W(t)} \qquad (4.19)$$

The random variable $ln\frac{S(t)}{S(0)}$ is normally distributed with mean $(\mu-\frac{1}{2}\sigma^2)t$ and variance $\sigma^2 t$. Future changes in value are independent of past changes in value.

4. Standard Error

The standard error (SE) is a measure of error. The forecasted standard error is calculated daily. It expressed by the difference between the actual value and forecasted value (Choong, 2012):

Error for any case i = Actual value – Forecasted value

$$e_i = A_i - f_i \qquad (4.20)$$

The standard error of all the techniques that used in this study is figured out, by the same way that is shown in equation (4.20).

4.5Comparison Techniques of Forecasting Accuracy

This part introduces the estimation of forecasting errors for making comparisons across time series; in order to evaluate the performance of the forecasting techniques.

The measures of forecasting accuracy that are used in this search are: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Theil Inequality Coefficient (U). In each of the forthcoming definitions, A_t is the actual value, f_t is the forecasted value, $e_t = A_t - f_t$ is the forecast error and n is the number of observations.

4.5.1 Root Mean Square Error

The Root Mean Square Error (RMSE) calculation is a well-known method of error analysis. It depends on the scale of measurement and also affected by data transformations. Therefore, the effects of positive and negative errors don't cancel out. In other words, the opposite signed errors do not offset one another, so it gives an overall idea of the error occurred during forecasting (Adhikari & Agrawal, 2013).

Statisticians say: forecasts are on the proper target; whenever the RMSE is as close to zero as possible. Generally speaking, it is a measure of the average squared deviation of forecasted values from actual ones. The general equation for RMSE is given as (Johnson, 1995):

$$RMSE = \sqrt{\sum \frac{e_t^2}{n}} \qquad (4.21)$$

4.5.2 Mean Absolute Error

Mean Absolute Error (MAE) is an error statistic that averages the absolute deviation of forecasted values from original ones. Thus, the effects of positive and negative errors do not cancel out. MAE also depends on the scale of measurement and data transformations. It should

be as small as possible; to obtain good forecast (Adhikari &Agrawal, 2013).

MAE is given by (Boiroju*et al*., 2011):

$$MAE = \frac{\sum |e_t|}{n} \quad (4.22)$$

4.5.3 Mean Absolute Percentage Error

Mean Absolute Percentage Error (MAPE)is another widely used accuracy measure in forecasting with non-negative actual observations. MAPE represents the percentage of average absolute error occurred; which is tended to reinforce the perception of inaccurate forecasts. The properties of MAPE are similar to those of MAE properties. It is given by the following equation (Swanson *et al*., 2011):

$$MAPE = \frac{1}{n} \cdot \sum \frac{|e_t|}{A_t} \quad (4.23)$$

4.5.4 Theil Inequality Coefficient

Thiel's Inequality Coefficient is known as Thiel's U.It is the ratios of the root mean squared errors to the root mean of the squared

forecasted values plus the root mean of the squared actual values (Rapach & Wohar, 2006).

In addition, it provides a measure of how well a time series of estimated values compares to a corresponding time series of observed values. This measure is affected by change of scale and data transformations. It is a normalized measure of total forecast error. The U statistic value is between $0 \leq U \leq 1$; the closer the value of U is to zero, the better the forecast method. A value of U=1 means the forecast is no better than a naive guess, while U = 0 means a perfect fit. The statistic measures the degree to which one time series differs from another. Thiel's U is calculated as (Adhikari & Agrawal, 2013):

$$U = \frac{\sqrt{\frac{1}{n} \cdot \sum (A_t - f_t)^2}}{\sqrt{\frac{1}{n} \cdot \sum f_t^2} + \sqrt{\frac{1}{n} . \sum A_t^2}} \qquad (4.24)$$

Chapter Five

Results and Discussion

Chapter Five

Results and Discussion

5.1 Introduction

This chapter presents the estimation results of the study and discusses its findings. It introduces a brief interpretation of the empirical forecasted results based on the model presented in the previous section; MCs, SMAs, and EMAs. The results will be presented numerically and graphically to show the discrepancy between the techniques from many sides.

5.2 Descriptive Statistics

Table 5.1 presents a summary descriptive statistics of the daily market index value, actual stock market returns and forecasted stock market returns estimated via the three forecasting techniques. The descriptive statistics cover the period (2003-2012).

Table (5.1)

Summary of Descriptive Statistics*

Variables	Mean	Median	Max	Min	SD
Index	**2378.061**	**2571.10**	**5043.70**	**1034.0**	**925.99**
Actual return	**0.0002**	**0.0005**	**0.0469**	**-0.0453**	**0.0103**
SMA 2 days	**0.0002**	**0.0004**	**0.0445**	**-0.0416**	**0.0081**
SMA 3 days	**0.0002**	**0.0003**	**0.0426**	**-0.0410**	**0.0067**
SMA 5 days	**0.0002**	**0.0003**	**0.0245**	**-0.0309**	**0.0053**
SMA 10 days	**0.0002**	**0.0002**	**0.0139**	**-0.0244**	**0.0039**
EMA 20%	**0.0002**	**0.0005**	**0.0421**	**-0.0427**	**0.0088**
EMA 30%	**0.0002**	**0.0004**	**0.0407**	**-0.0405**	**0.0080**
MCs	**0.0002**	**0.0004**	**0.0512**	**-0.0530**	**0.0107**

*Source: prepared by the researcher based on Eviews 5.

Focusing on MCs technique, the descriptive statistics show that the standard deviation estimated to be (0.0107); which is a slightly higher than standard deviation of actual returns by only (0.0004) digits. But at the same time, it's the closest value to the actual returns. Meaning that, there is a kind of harmony in data distribution. MCs technique provides the most accurate explanation of the data dispersion and remoteness from the mean. This proves that this technique can present a very good clue about market trends. While the mean of MCs technique is similar to

actual returns as the same as all techniques. However, the maximum value of MCs equals (0.0512) while minimum value equals (-0.0530).

In addition, the EMA of damping coefficient 20% gives a standard deviation equals 0.0088, which is considered slightly low comparing to the MCs standard deviation. It has a maximum value of (0.0421) and minimum value of (-0.0427).

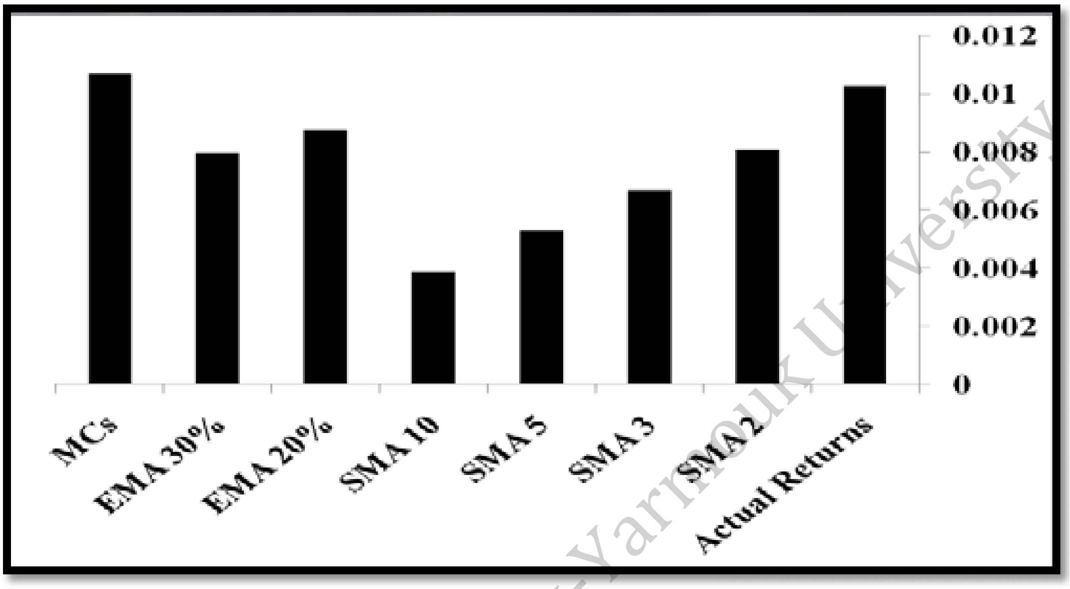
Then EMA of damping coefficient 30% is ranked at the third level; where the standard deviation equals (0.0080). The maximum value equals (0.0407) and minimum value equals (-0.0405). It is worth to mention that, the median of all techniques show close values to the median of actual returns (0.0005).

Moreover, SMA of 2-days has (0.0081) standard deviation, with maximum value of (0.0445) and minimum value of (-0.0416). On the other hand, among all the used techniques SMA of 10-days gives the lowest and farthest value of standard deviation, estimated to be (0.0039). Its maximum value estimated to be (0.0139) and minimum value equals (-0.0244).

The following Figure 5.1 represents all the standard deviations results for all the various techniques used in this study.

Figure (5.1)

Standard Deviation of Techniques



5.3Forecasting Results

The following section provides an analysis of the forecasting error results, in order to compare the forecasting ability of the different techniques. Table 5.2 reports the four accuracy measures (RMSE, MAE, MAPE, U) for the all forecasting techniques (SMA of 2-days, SMA of 3-days, SMA of 5-days, SMA of 10-days, EMA of 20% damping factor, EMA of 30% damping factor, and MCs).The figures 5.2, 5.3, 5.4, and 5.5 show the results in a graphical manner.

In the four accuracy measures (RMSE, MAE, MAPE, U), the closer the measure to zero, the more accurate is the technique. It can be

seen from Table 5.2 that MCs technique has relatively the best prediction accuracy comparing to the other six techniques.

Table (5.2)
Summary of Analysis Results of Four Accuracy Measures*

Variables	RMSE	MAE	MAPE	U
SMA 2	**0.0064**	**0.0043**	**2.5549**	**0.3483**
SMA 3	**0.0082**	**0.0055**	**2.8845**	**0.4800**
SMA 5	**0.0090**	**0.0061**	**2.3521**	**0.5774**
SMA 10	**0.0097**	**0.0066**	**1.8978**	**0.6878**
EMA 20%	**0.0120**	**0.0081**	**4.4935**	**0.6321**
EMA 30%	**0.0117**	**0.0079**	**4.1405**	**0.6404**
MCs	**0.0031**	**0.0022**	**1.4551**	**0.1494**

*Source: prepared by the researcher.

MCs technique shows the lowest values of RMSE, MAE, MAPE, and U comparing to all six forecasting techniques. Thus we accept H_1 and H_2; that MCs is more accurate in predicting stock market returns of ASE over the period (2003-2012) than the SMA and EMA techniques. Furthermore, the techniques are arranged in a descending order from the lowest RMSE to those with the highest RMSE as follows: MCs, SMA of 2-days, SMA of 3-days, SMA of 5-days SMA of 10-days, EMA of damping factor 30%, and finally EMA of damping factor 20%. The values of their corresponding RMSE are respectively, 0.0031, 0.0064,

0.0082, 0.0090, 0.0097, 0.0117, and 0.0120. The results are consistent based on MAE measure, but with different values as follows: 0.0022, 0.0043, 0.0055, 0.0061, 0.0066, 0.0079, and 0.0081.

In contrast, MAPE gives slightly different results. The techniques are arranged in a descending order from the lowest MAPE to those with the highest MAPE as follows: MCs, SMA of 10-days, SMA of 5-days SMA of 2-days, SMA of 3-days, EMA of damping factor 30%, and EMA of damping factor 20%. The values of their corresponding MAPE are respectively, 1.4551, 1.8978, 2.3521, 2.5549, 2.8845, 4.1405, and 4.4935.

Likewise, Theil Inequality Coefficient technique (U) provides different results from the previous measures. The techniques are arranged in a descending order from the lowest U to those with the highest U as follows: MCs, SMA of 2-days, SMA of 3-days, SMA of 5-days, EMA of damping factor 20%, EMA of damping factor 30%, and SMA of 10-days. The values of their corresponding MAPE are respectively, 0.1494, 0.3483, 0.4800, 0.05774, 0.06321, 0.06404, and 0.06878. But, all in all it seems that all the forecasting accuracy results are closed to each other's. The figures 5.2, 5.3, 5.4, and 5.5 confirm our results. MCs shows the lowest value of RMSE, MAE, MAPE, and U. Indicating that, it is the most accurate forecasting technique.

Figure (5.2)

RMSE - Results

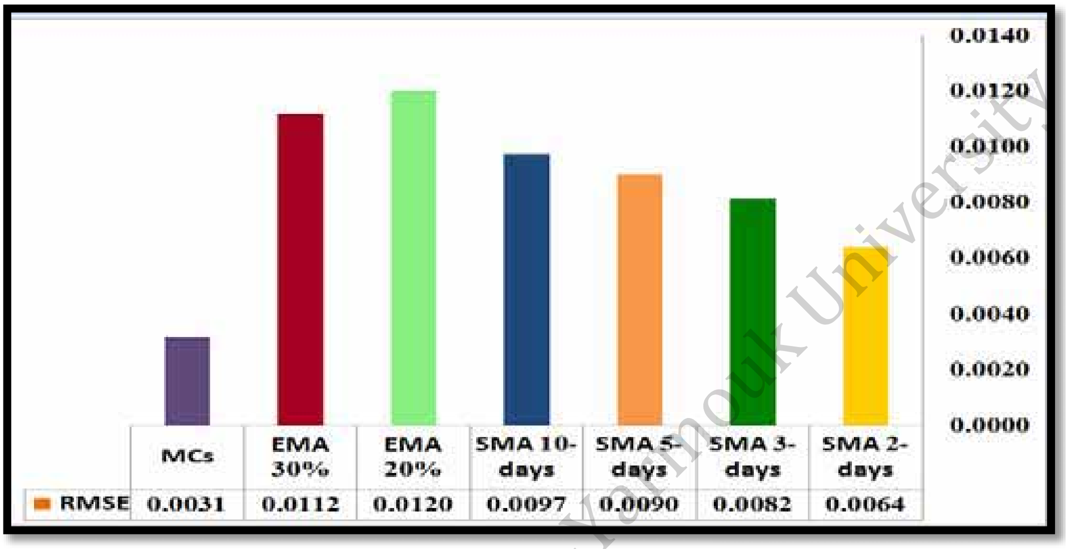


Figure (5.3)

MAE - Results

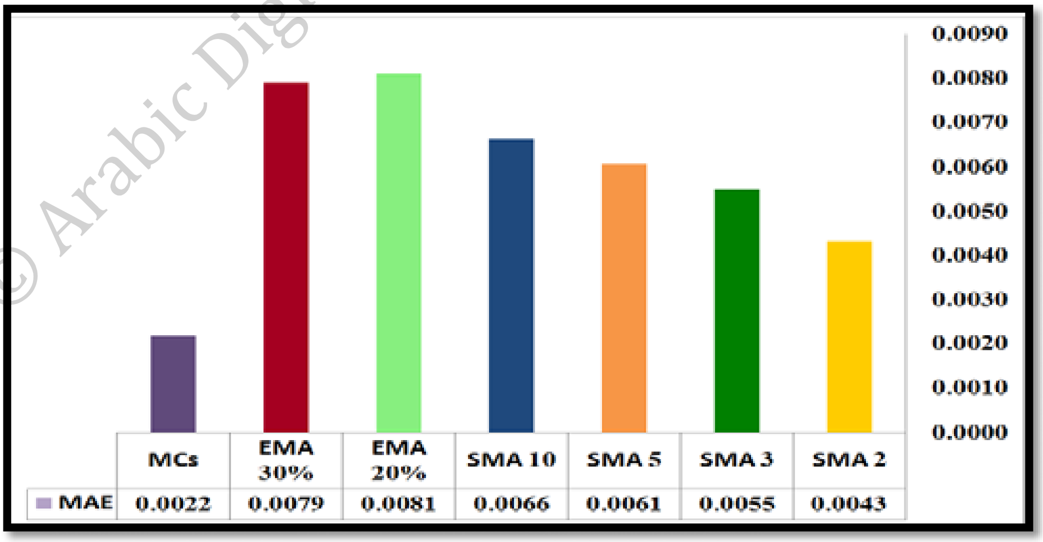


Figure (5.4)

MAPE - Results

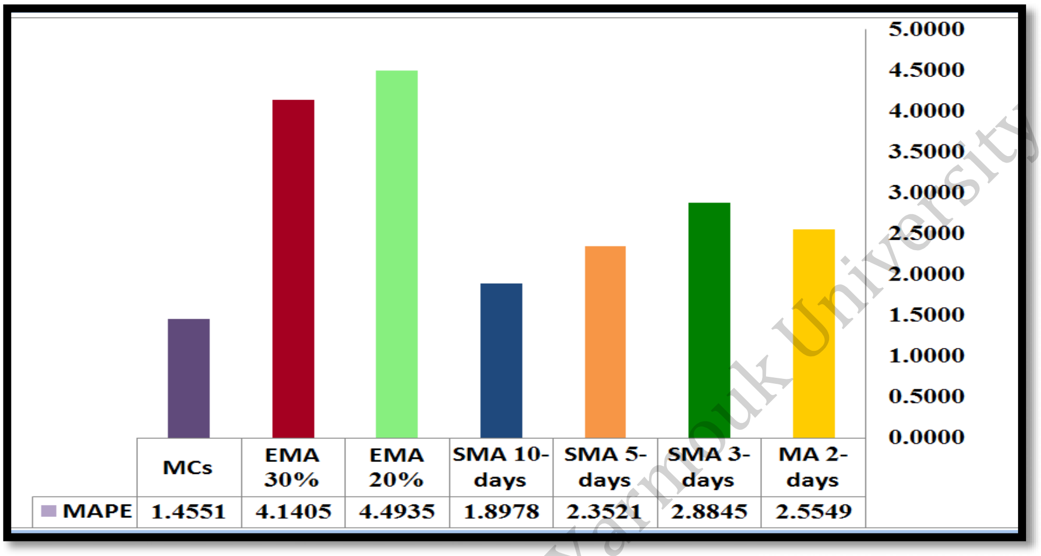
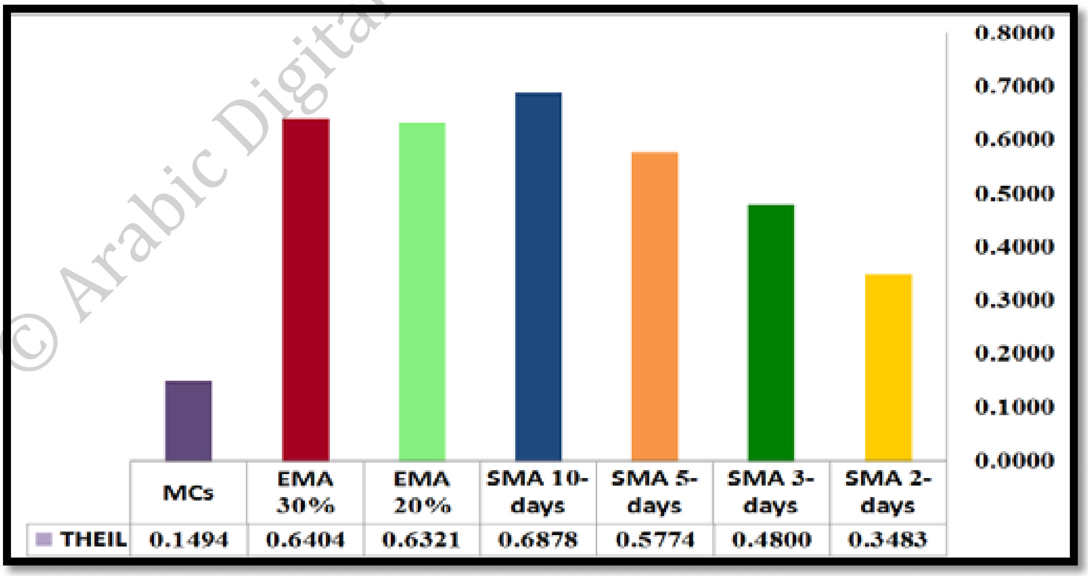


Figure (5.5)

U – Results



5.4 Empirical Forecasted Returns

In order to forecast returns during the period 2003-2012; the three forecasting techniques are applied as explained in the previous chapter. The results of the three techniques are presented graphically by implementing monthly averages of return.

First, figures 5.6, 5.7, 5.8, and 5.9 represent the monthly averages of actual returns compared with the monthly averages of forecasted returns estimated using: SMA of 2, 3, 5, and 10-days. The figures show that the forecasted returns don't exactly match the actual returns line. It means that the forecasted stock market returns which flow from different MAs are slightly over-performing or under-performing the actual returns over time.

Figure (5.6)

Forecasted vs. Actual Returns using SMA of 2-days

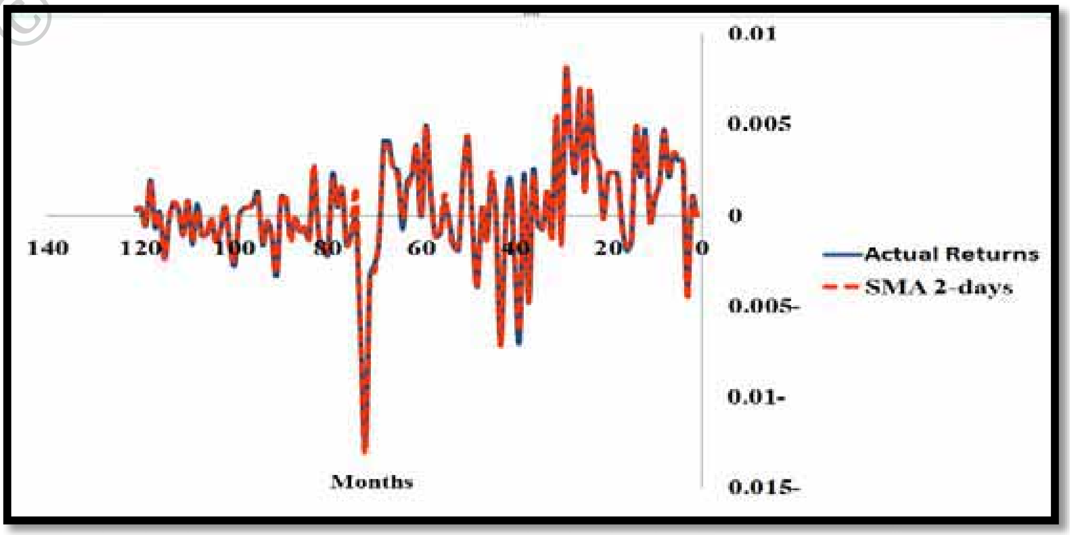


Figure (5.7)

SMA of 3-days vs. Actual Returns

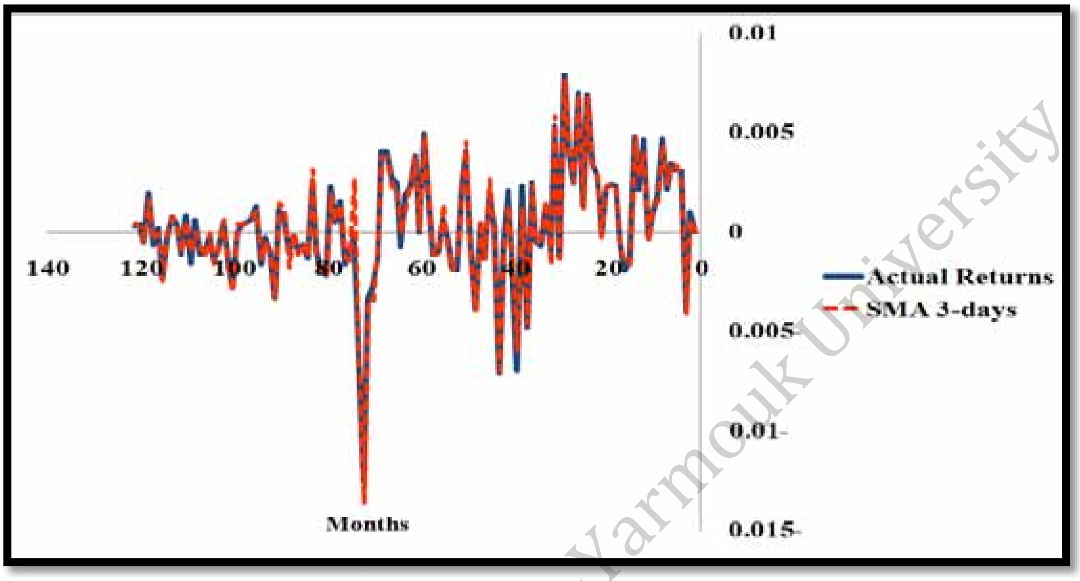


Figure (5.8)

SMA of 5-days vs. Actual Returns

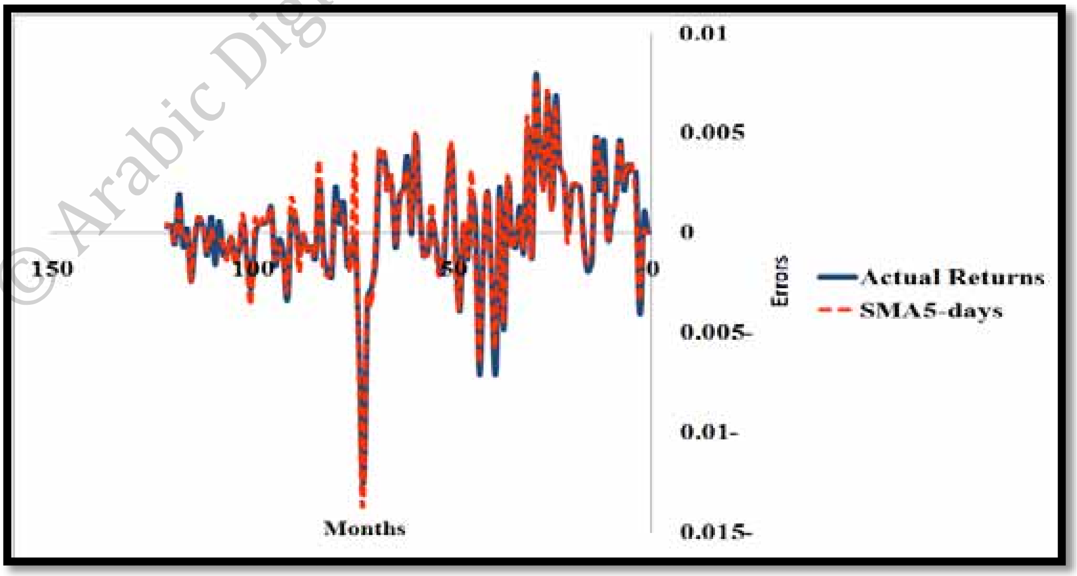
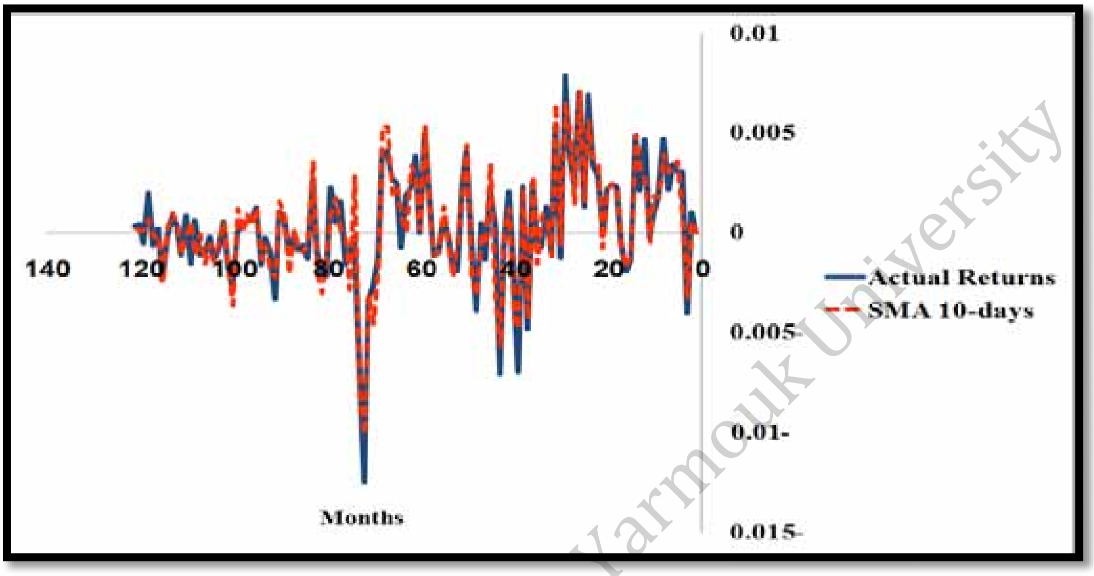


Figure (5.9)

SMA of 10-days vs. Actual Returns



Second, Figures 5.10 and 5.11 represent the EMA of damping factor 20% and 30% respectively. They represent the monthly averages of EMA compared to monthly actual returns. They also reflect some different values from actual returns.

Figure (5.10)

EMA of (20%) vs. Actual Returns

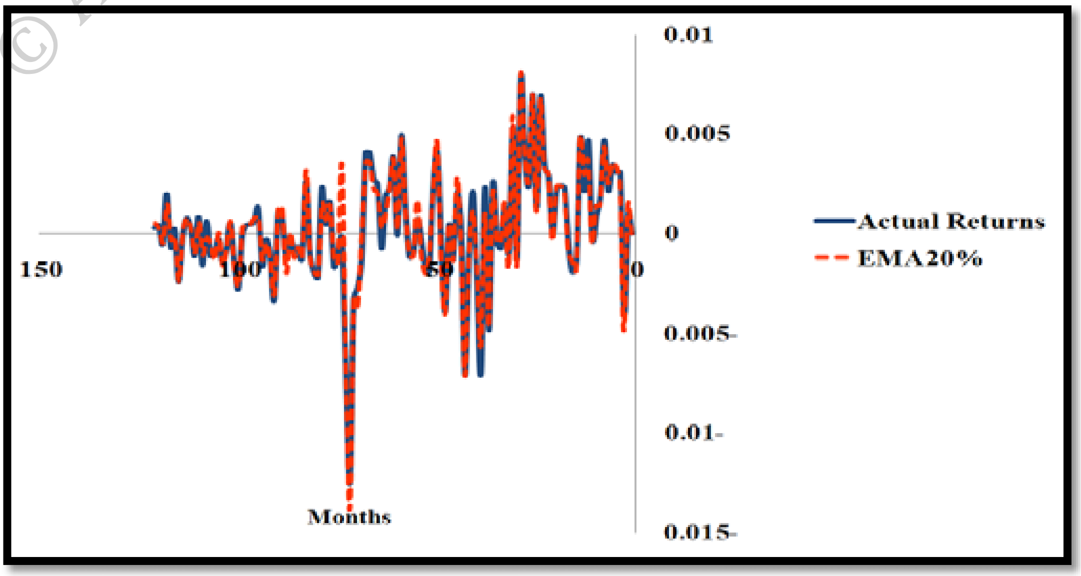
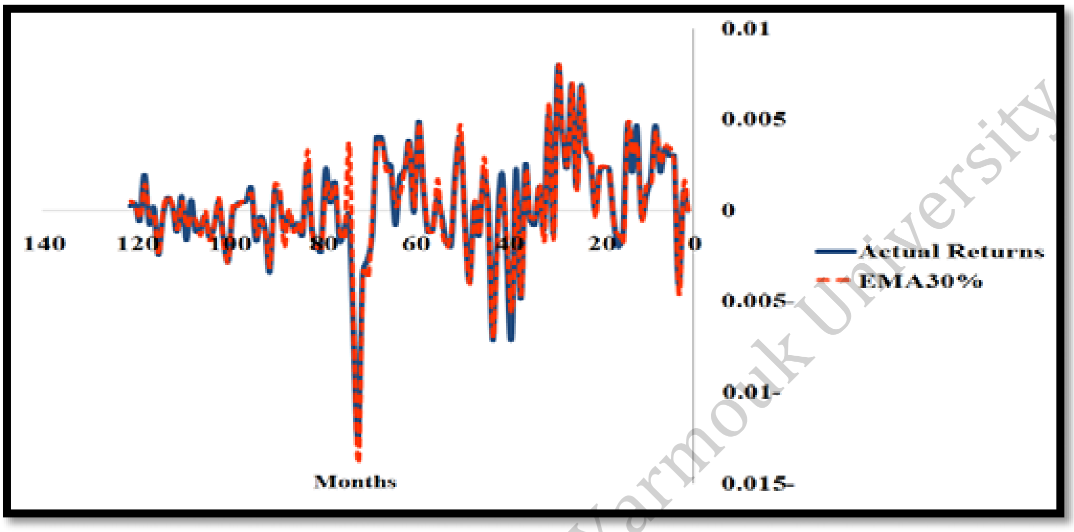


Figure (5.11)

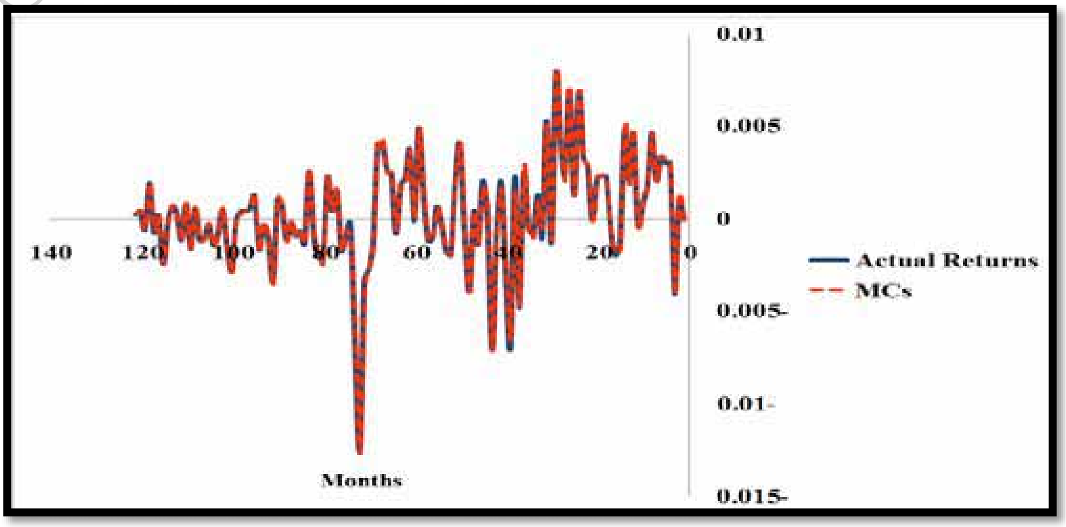
EMA of (30%) vs. Actual Returns



Third, Figure 5.12 represents the monthly averages of MCs return compared to the monthly averages of actual return. It shows that it has the lowest lag compared with all others techniques. Therefore, the results show that the most accurate technique that gives the closest results to the real returns is MCs.

Figure (5.12)

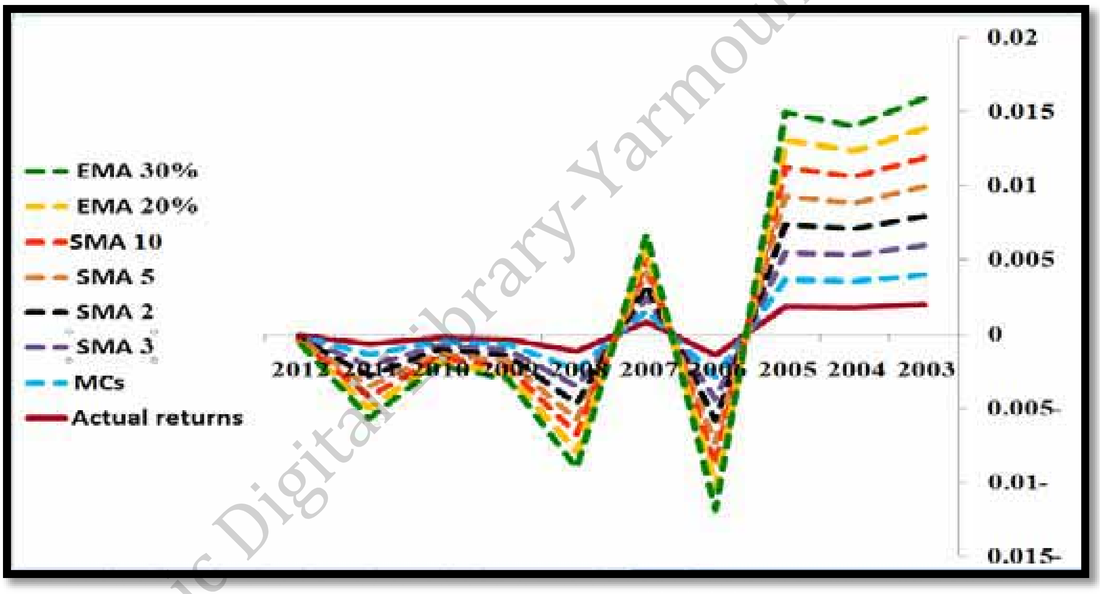
MCs vs. Actual Returns



For more clarifying, figure 5.13 represents the yearly forecasted returns for all forecasting techniques compared with actual returns. It also shows consistent results but in an alternative manner.

Figure (5.13)

Yearly Forecasted Returns vs. Actual Returns



5.5 Results of Hypotheses Testing

In the light of the previous results and empirical studies, which are accomplished in ASE as: Atmeh and Dobbs (2006), Ajlouni and Al-Hawarei (2010), Ali *et al*. (2011), Al-khatib and Al-Horani (2012), and AL- Shubiri (2013) who conclude that ASE is not efficient at the weak level. The results of hypotheses testing are as follows:

- The first hypothesis states that "MCs is more accurate in forecasting stock market returns than SMA techniques". It is found that Monte Carlo technique gives a superiority and significant ability in predicting stock market returns. As a result, the hypothesis is accepted.
- The second hypothesis states that "MCs is more accurate in forecasting stock market returns than EMA techniques". It is also found that MCs technique gives more accurate results than EMA ones. Therefore the hypothesis is accepted.

As a result of the previous results obtained, the following chapter provides a summary for the main results in addition to the recommendations and suggestions for further research.

Chapter Six

Conclusions and Recommendations

Chapter Six
Conclusions and Recommendations

6.1 Conclusions

This study investigates the forecasting ability of three forecasting techniques in predicting the stock market returns of ASE over the period (2003- 2012). In fact, the techniques which are used include four-MAs techniques, two- EMAs techniques, and MCs. The forecasting ability is estimated via four accuracy measures based on the error term (the difference between the actual and forecasted returns). These measures include: RMSE, MAE, MAPE, and U. The results can be summarized as follows:

1. Technical analysis techniques were useful to predict stock returns by utilizing time series data.

2. The results indicate that Monte Carlo technique has a superior ability to predict stock market returns.

3. According to forecasting accuracy measures: RMSE, MAE, MAPE, and U; the forecasting techniques are arranged from the most accurate to the least as: MCs, MA, and finally EMA.

4. Amman Stock Exchange seems to be inefficient at the weak level, because the market can be predicted using technical analysis

techniques. Therefore, investment strategies can be utilized and investors are able to choose when to buy or sell according to these strategies.

6.2 Recommendations and Suggestions for Future Research

Based on our results,

1. we recommend both academicians and investors to use MCs to make the best forecast for ASE stock market returns.

2. we recommend both academicians and investors to develop their investment strategies based on MCs return forecasts.

3. we recommend investors in ASE to use technical analysis which is based on historical trading data to predict future returns and beat the market given that it is inefficient at the weak level.

4. Future research can develop more accurate forecasting techniques to predict stock returns.

5. Future research can develop investment strategies based on technical analysis to beat the market.

6. Future research can use more advanced versions of MCs to forecast stock prices.

7. Future research can conduct an out of sample forecasting of ASE stock prices.

List of References

A- Articles:

Al-khatib, H. and Al-Horani, A. 2013.Predicting financial distress of public companies listed in Amman Stock Exchange. *European Scientific Journal*.8 (15).

Ali, S. Abu Hammad, A. Samhouria, M. and Al-Ghandoora, A. 2011. Modeling stock market exchange prices using Artificial Neural Network: A study of Amman Stock Exchange. *Jordan Journal of Mechanical and Industrial Engineering*. 5 (5): 439 – 446.

Atmeh, M. and Dobbs, I. 2006. Technical analysis and the stochastic properties of the Jordanian stock market index return. 23 (2):119 – 140.

Alrabadi, D. 2012. Short-term stock price reaction to shocks: Evidence from Amman Stock Exchange. *Interdisciplinary Journal of Contemporary Research in Business*. 4(1).

Assaleh, K. El-Baz, H. and Al-Salkhadi, S. 2011.Predicting stock prices using polynomial classifiers: The case of Dubai financial market. *Journal of Intelligent Learning Systems and Applications*. 3, 82-89.

Belke, A. and Polleit, T. 2004. Dividend yields for forecasting stock market returns a cointegration analysis based on the ARDL approach. *Inst. für Volkswirtschaftslehre*. 244, 1-22.

Bernard, V. and Thomas, J. 1990. Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. *Journal of Accounting and Economics*. 13, 305-340.

Boiroju, N. Yerukala, R. Rao, M. and Reddy, M. 2011. A bootstrap test for equality of mean absolute errors. *Journal of Engineering and Applied Sciences Asian Research Publishing Network (ARPN)*. 6(5).

Boyle, P. Broadie, M. and Glasserman, P. 1997. Monte Carlomethods for security pricing. *Journal of Economic Dynamics and Control*. 21: 1267-1321.

Caflisch, R. 1998. Monte Carlo and Quasi - Monte Carlo methods. *Acta Numerica, CambridgeUniversity Press*. PP. 1-49.

Choi, J. Hauser, S. and Kopecky, K. 1999. Does the stock market predict real activity? Time series evidence from the G-7 countries. *Journal of Banking and Finance*. 23, 1771-1792.

Cohen, G. Kudryavtsev, A. and Hon-Snir, S. 2011. Stock market analysis in practice: Is it technical or fundamental? *Journal of Applied Finance & Banking*. 1 (3): 125-138.

De Bondt, W. and Thaler, R. 1985. Does the stock market overreact? *The Journal of Finance*. 40, 793-805.

Döpke, J. Hartmann, D. and Pierdzioch, C. 2008. Real-time macroeconomic data and ex ante stock return predictability. *International Review of Financial Analysis*. 17, 274- 290.

Elbarghouthi, S. Yassin, M. and Qasim, A. 2012.Is Amman Stock Exchange an Efficient Market? *International Business Research*.5(1).

Elleuch, J. 2009. Fundamental analysis strategy and the prediction of stock returns. *International Research Journal of Finance and Economics*. 30.

Fama, E. 1965. Random walks in stock market prices, *Financial Analysts Journal*. 16. [a].

Fama, E. 1965. The behavior of stock-market prices.*The Journal of Business*. 38 (1): 34-105. [b].

Fama, E. 1970. Efficient capital markets: A review of theory and empirical work source. *The Journal of Finance*. 25 (2): 383-417.

Ferreira, M, A. and Santa-Clara, P. 2011. Forecasting stock market returns: The sum of the parts is more than the whole. *Journal of Financial Economics*. 100, 514- 537.

Giovanis,E. 2011. GARCH -Monte-Carlo simulation models with wavelets decomposition algorithm for stock returns prediction. *International Journal of Computer Information Systems*. 2 (3).

Gupta, R. and Modise, M. 2012. South African stock return predictability in the context data mining: The role of financial variables and international stock returns. *Economic Modelling*. 29, 908–916.

Hartmann, D. and Pierdzioch, C. 2007. Exchange rates, interventions, and the predictability of stock returns in Japan. *Journal of Multinational Financial Management*. 17, 155–172.

Halton, J. 1970. A Retrospective and a prospective survey of the Monte Carlo Method. *SIAM Journal on Applied Mathematics*. 12 (1).

Ito, T. 1990. Foreign exchange rate expectations: Micro survey data. *American Economic Review*. 80 (3): 434–449.

James, F. 1980. Monte Carlotheory and practice. *The Institute of Physica*. 43.

Kara, Y. Boyacioglu, M. and Baykan, O.2011. Predicting direction of stock price index movement using Artificial Neural Networks and Support Vector Machines: The sample of the Istanbulstock exchange. *Expert Systems with Applications*. 38, 5311–5319.

Kim, K. 2003. Financial Time Series Forecasting Using Support Vector Machines. *Neuro computing*. 55, 307 – 319.

Koopman, S, J. Jung backer, B. and Hol, E. 2005. Forecasting daily variability of the S&P 100 stock index using historical, realised and implied volatility measurements. *Journal of Empirical Finance*. 12, 445– 475.

Lewellen, J. 2004. Predicting returns with financial ratios. *Journal of Financial Economics*.74, 209–235.

Lo, W, A. 2007. Efficient Markets Hypothesis. *The New Palgrave: A Dictionary of Economics, Palgrave McMillan, New York*. pp. 1-28.

Malkiel, B. 1989. Is the stock market efficient? *American Association for the Advancement of Science*. 243 (4896): 1313-1318.

Malkiel, B. 2003. The efficient market hypothesis and its critics. *Journal of Economic Perspectives*. 17 (1): 59 – 82.

Metropolis, N. 1987. The beginning of the Monte Carlo method. *Los Alamos Science*.

Okpara, G. 2010. Stock market prices and the random walk hypothesis: Further evidence from Nigeria. *Journal of Economics and International Finance*. 2 (3): 049-057.

Rapach, D, E. Wohar, M, E. and Rangvid, J. 2005. Macro variables and international stock return predictability. *International Journal of Forecasting*. 21,137– 166.

Rapach, D, E. Wohar, M, E. and Rangvid, J. 2006. In-Sample vs. Out-of-Sample tests of stock return predictability in the context of data mining. *Journal of Empirical Finance*. 13, 231-247.

Shubita, M. 2013. The Forecasting Ability of Earnings and Operating Cash Flow. *Interdisciplinary Journal of Contemporary Research in Business*.5 (3).

Swanson, D. Tayman, J. and Bryan, T. 2011. MAPE-R: A rescaled measure of accuracy for cross- sectional forecasts. *Journal of Population Resarech*, *Springer*. 28, 225-243.

Thaler, R. 1987. Anomalies: The January effect. *Journal of Economic Perspectives*. 1 (1): 197-201.

Tsao Pan, W. 2010. Performing stock price prediction use of hybrid model. *Emerald Group Publishing Limited*. 4 (1): 77 – 86.

Whiteside II PE, J. 2008. A practical application of Monte Carlo simulation in forecasting. *AACE International Transactions*. 4.

B- Books:

Adhikari, R. and Agrawal, R.2013.*An Introductory Study on Time Series Modeling and Forecasting*. LAMBERT Academic Publishing, Germany.

Bachelier, Louis (1900) trans. James Boness. *Theory of Speculation*, in Cootner (1964) The *Random Character of Stock Market Prices*. MIT Press. pp. 17-78.

Barreto, H. and Howland, F. 2006. *Monte Carlo Simulation. In: Introductory Econometrics: Using Monte Carlo Simulation with Microsoft Excel*, Cambridge University Press, New York, N.Y., USA, PP. 215- 235.

Boas, M. 1996. *Probability. In: Mathematical Methods in the Physical Sciences*, (2nd Ed.) John Wiley & Sons, Canada, PP. 685-737.

Bodie, Z. Kane, A. and Marcus, A. 2013.*The Efficient Market Hypothesis. In: Essential of Investments*, (10th Ed.) Mc-Graw Hill/Irwin, New York, N.Y., USA, PP. 228- 259.

Brooks, J. 2006. *Moving Averages. In: Mastering Technical Analysis Using the Tools of Technical Analysis for Profitable Trading*, McGraw-Hill, USA, PP. 115-131.

Brown, C. 2003.*What Is Technical Analysis, and Who Uses It? In: All about Technical Analysis: The Easy Way to Get Started*, Mc-Graw Hill/Irwin, New York, N.Y., USA, PP. 17-26.

Cootner, P. 1964. *The Random Character of Stock Market Prices*, Cambridge M.I.T.

Earl, D. and Deem, M. 2008. *Monte Carlo Simulations. In Methods in Molecular Biology,(vol. 443), Molecular Modeling of Proteins, edited by Andreas Kukol,* Humana Press, Totowa, NJ, PP. 25-36.

Feller, W. 1971.*An Introduction to Probability Theory and its Applications,*(Vol.II)John Wiley & Sons Inc., New York

Glasserman, P. 2003. *Principles of Monte Carlo. In: Monte Carlo Methods in Financial Engineering (Stochastic Modelling and Applied Probability),* Springer, USA, PP.1-36.

Leeuwaarden, J. and der Pol, J. 2011.*Simulating Geometric Brownian Motion. In: Monte Carlo Simulation with Applications to Mathematical Finance.* Eindhoven University of Technology, The Netherlands, PP. 66-73.

Malkiel, B. 1999. *How The Pros Play The Biggest Game in Town. In: A Random Walk Down Wall Street: Including A Life-Cycle Guide To Personal Investing*. W. W. Norton & Company, New York, N.Y., USA, PP. 117- 195.

Mendelsohn, B. 2000.*Today's Markets Have Changed—Why Trend Forecasting. In: Trend Forecasting With Technical Analysis: Unleashing the Hidden Power of Intermarket Analysis to Beat the Market*. Marketplace Books, USA, PP.59-69.

McDonald, M. 2007. *Fundamental Analysis vs. Technical Analysis. In: FOREX Simplified: Behind the Scenes of Currency Trading.* Marketplace Books Glenelg Maryland, USA, pp.19-32.

Robert, C. and Casella, G. 2010. *Introduction to Monte Carlo Methods. In: Introducing Monte Carlo Methods with R.* Springer, New York, N.Y., USA, PP. 1-30.

Rollett, A., and Manohar, P. 2004. *The Monte Carlo Method. In: Continuum Scale Simulation of Engineering Materials*. Wiley-VCH , Weinheim, Germany, PP, 76-113.

C- Conference:

AL- Shubiri, F. 2013. *Analysis of the Relationship between Economic Forces and Abnormal Stock Return: Empirical Evidence*. Department of Finance and Banking, Amman Arab University-Jordan. Proceedings of the April 24th -25th on The 9th International Scientific Conference, Zarqa University, Jordan. Pp 1-10.

Chen, N., and Hong, L. 2007. *Monte Carlo Simulation in Financial Engineering*. Department of Systems Engineering and Industrial Engineering. Proceedings of the December 9th -12nd on Winter Simulation Conference, Washington, DC, USA. Pp 919-931.

Kheradyar, S. and Ibrahim, I. 2011. *Financial Ratios as Empirical Predictors of Stock Return*. Graduate School of Business, National University of Malaysia. Proceeding in the International Conference on Sociality and Economics Development. IACSIT Press, Singapore. Pp 318-322.

Malkiel, B. 2011. *The Efficient-Market Hypothesis and the Financial Crisis.* Proceedings of the 28th Russell Sage Conference. Princeton University, Princeton, USA. Pp 1-59.

D- Dissertations:

Al-Hawarei, Mohammad 2010. *The Predictability of Stock Returns using (First-Order Serial Correlation): Evidence from Amman Stock Exchange during the Period 01/0l/2001 – 29/05/2008*. Department of Banking and Finance, Faculty of Economic and Administrative Sciences, Yarmouk University, Irbid, Jordan.

Lafortune, Eric 1996. *Mathematical Models and Monte Carlo Algorithms for Physically Based Rendering*. Department of Computer Science, Faculty of Engineering Katholieke University of Leuven, Leuven, Belgium.

Johnson, Larry 1995. *A Comparison of Methods for Estimating RMS Error:A "Brute Force" Approach Versus a Mathematically-Elegant Approach, as Applied to the Calculation of a Specific Retrieval Error for a Limb-Scanning Microwave Radiometer-Spectrometer*. Department of the Air Force, School of Engineering Air University, Ohio, USA.

Kroese, Dirk2011. *Monte Carlo Methods*. Department of Mathematics, University of Queensland, state of Queensland, Australia.

Krykova, Inna 2003. *Evaluation of Path- Dependent Securities with Low Discrepancy Methods*. Department of Science, Worcester Polytechnic Institute Worcester, USA.

Toms, Marcus 2011. *The Technical Analysis Method of Moving Average Trading: Rules That Reduce the Number of Losing Trades*. Department of Electrical, Electronic and Computer Engineering Newcastle University, Newcastle upon Tyne, United Kingdom.

Zhang, Yingjian 2004. *Prediction of Financial Time Series with Hidden Markov Models*. Department of Applied Science, SimonFraser University, Canada.

E- Web Site with an author or an organization

Belgin Sert, M. 2011. *Option Pricing with Monte Carlo Integration*. Retrieved April. 12, 2013 from the World Wide Web: http://mcs.cankaya.edu.tr/proje/2011/yaz/merve_damla/Rapor.pdf

Cargal, M, J. 1988. *Recursion and Averages. In: Discrete Mathematics for Neophytes: Number Theory, Probability, Algorithms, and Other Stuff.* Retrieved May. 16, 2013 from the World Wide Web: http://www.cargalmathbooks.com/32%20Averages%20.pdf

Choong, J. 2012. *Powerful Forecasting with MS Excel*. Retrieved Feb.16, 2013 from the World Wide Web: http://www.xlpert.com/ebook/Powerful_Forecasting_With_MS_Excel_sample.pdf

Cowan, G. 2009. *Monte Carlo Techniques*. Royal Holloway, University of London. Retrieved Mar. 16, 2013 from the World Wide Web:http://www.amrcaseinfo.com/pdflib/518_15463.pdf

Das, S. 2010. *Quantitative Methods for Finance*. Retrieved April. 9, 2013 from the World Wide Web: http://algo.scu.edu/~ sanjivdas/q115/Q115.pdf

Davidian, M. 2005. *Simulation Studies in Statistics*. Retrieved Sep. 9, 2013 from the World Wide Web: http://www4.stat.ncsu.edu/~ davidian/st810a/simulation_handout.pdf

Fanning, S. and Parekh, J. 2004. *Stochastic Processes and their Applications to Mathematical Finance*. Retrieved June. 4, 2013 from the World Wide Web:

http://www.math.umd.edu/undergraduate/majors/pastundergradresearch/files/fanningparekh.pdf

Ibbotson Associates, 2005. *Monte Carlo Simulation*. Retrieved Feb. 24, 2013 from the World Wide Web: http://advisor.morningstar.com/Principia/pdf/Monte%20carlo%20White%20Paper%20Ibbotson.pdf.

Lapeyre, B. 2007. *Introduction to Monte-Carlo Methods*. University of Halmstad. Retrieved Oct. 9, 2013 from the World Wide Web: http://cermics.enpc.fr/~bl/Halmstad/monte-carlo/lecture-1.pdf.

Perros, H. 2009.*Computer Simulation Techniques: The definitive introduction!* Retrieved Sep. 24, 2013 from the World Wide Web:http://www.csc.ncsu.edu/faculty/perros//simulation.pdf

Shachmurove, Y., BenZion, U., Klein,P., and Yagil, J. 2001. *A Moving Average Comparison of the Tel-Aviv 25 and S & P 500 Stock Indices*. Retrieved Feb. 24, 2013 from the World Wide Web:www.researchgate.net/...SP_500...Tel-Aviv_25_Indices

Umrigar, C. 2010. *Monte Carlo Methods*. Physics Department, Cornell University, Ithaca. Retrieved Mar. 16, 2013 from the World Wide Web:http://pages.physics.cornell.edu/~sethna/teaching/ComputationalPhysics/LectureScans/CyrusMonteCarlo.pdf

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الملخص

ندى إبراهيم أبوالجرايش. التنبؤ بعوائد الأسهم بواسطة مُحاكاة مونتي كارلو: حالة بورصة عمان للأوراق المالية. رسالة ماجستير بقسم العلوم المالية و المصرفية. جامعة اليرموك 2013.
(المشرف: د. ديما وليد الربضي).

تقوم هذه الدراسة بإختبار قدرة محاكاة مونتي كارلو على التنبؤ بعوائد الأسهم في بورصة عمان للأوراق المالية. و بالتحديد فإننا نقارن قدرة التنبؤ (داخل العينة) لمونتي كارلو مع طرق المتوسطات المتحركة البسيطة و الأسية. تتكون بيانات الدراسة من القيم اليومية للمؤشر العام للأسهم الحرة لبورصة عمان للأوراق المالية على الفترة (2003-2012). تقاس قدرة دقة التنبؤ من خلال أربعة مقاييس و هي: الجذر التربيعي لمعدل مربع الخطأ و المعدل المطلق لمعامل الخطأ و العدل المطلق النسبي لمعامل الخطأ و معامل تايل لعدم المساواة. تشير النتائج إلى أن محاكاة مونتي كارلو هي أدق طريقة تنبؤ من بين الطرق المدروسة. إضافةً إلى ذلك فإنه يبدو بأن بورصة عمان للأوراق المالية غير كفؤة على المستوى الضعيف و يُعزى هذا إلى قدرة المستثمرين على التنبؤ بعوائد الأسهم بإستخدام طرق التحليل الفني.

الكلمات المفتاحية: فرضية كفاءة السوق ، المتغيرات العشوائية، التنبؤ داخل العينة، مُحاكاة مونتي كارلو، المتوسط المتحرك البسيط، المتوسط المتحرك الأسي، هندسية الحركة البروانية، بورصة عمان للأوراق المالية .